WIND SPEED ESTIMATION USING NEURAL NETWORKS

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WIND SPEED ESTIMATION USING NEUERAL NETWORKS

A Thesis Submitted In the Partial Fulfillment of the Requirements for the Degree Of

Master of Technology

In

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By

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Dedicated to my beloved parents

And my sisters

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Prangya Parimita Pradhan
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CERTIFICATE

This is to certify that the dissertation entitled **"WIND SPEED ESTIMATION USING NEURAL NETWORKS"** being submitted by **Ms. Prangya Parimita Pradhan**, **Roll No. 211EE2381**, in partial fulfillment of the requirements for the award of degree of **Master Of Technology In Electrical Engineering (POWER CONTROL & DRIVES)** to the **National Institute of Technology**, **Rourkela**, is a bonafide record of work carried out by her under my guidance and supervision.

Date:

Place: Rourkela

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ABSTRACT

In electrical power system, prediction of Renewable energy sources has become essential for designing a control strategy to manage the electricity on the grid, which means scheduling of power production in advance to respond the load profile. It is very much essential to forecast wind power accurately, to help the system operators, to include wind generation into economic scheduling, unit commitment, and reserve allocation problems [4].

Basically neural network is aimed for short-term forecasting problems as it is capable to learn non-linear relationship between inputs and outputs by a non-statistical approach and don't require any predefined mathematical model. This thesis investigates the effectiveness of recurrent wavelet neural network (RWNN) and artificial wavelet neural network (AWNN) dynamics for wind speed forecasting. We evaluate the RWNN and AWNN against multilayer feed-forward neural network. The RWNN and AWNN are trained using back propagation gradient descent algorithm. The experimental results show that the performance of RWNN and AWNN approaches outperforms the multilayer feed-forward neural network. All the three models use Hourly averaged time series data (2982 numbers of samples) for wind speed collected from the National Renewable Energy Laboratory (NREL) [1].

Multi-resolution analysis of wind series is carried out using Least Asymmetry-8 wavelet and scaling filter for maximum overlap discrete wavelet techniques (MODWT) and for (discrete wavelet techniques (DWT) the mother wavelet chosen is Daubechies4(db4) wavelet . Both the wavelet techniques has been studied with the wind speed data and it is found that for estimation of wind speed, it is more preferable to choose MODWT technique as there may be the possibility of loss of information in the decomposed signal with the DWT as in each decomposition process the sample length reduced to half of the original sample length. Then each level decomposed signal is allowed to pass through different wavelet neural networks. Simulation is done in MATLAB SIMULINK environment. From the entire three neural networks, RWNN gives better results (in terms of mean absolute error as a performance index) as compared to other two methods (AWNN and multi-layer feed forward neural network).

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ACRONYMS

NWP	Numerical weather prediction
NN	Neural network
ANN	Artificial neural network
WT	Wavelet transform
FT	Fourier transform
MRA	Multi-resolution analysis
STFT	Short time Fourier transform
CWT	Continuous wavelet transform
DWT	Discrete wavelet transform
MODWT	Maximum overlap discrete wavelet transform
ACF	Autocorrelation function
BPA	Back-propagation algorithm
AWNN	Artificial wavelet neural network
WNN	Wavelet neural network
RWNN	Recurrent wavelet neural network
MSE	Mean square error
MAE	Mean absolute error

CHAPTER 1
Introduction

1.1 Background

It is well known that fossil fuels are being depleted at a very fast rate which motivates to supplement the power generation from the renewable sources such as wind, solar, tidal and fuel cells etc. Among the several renewable power generating systems, the wind power generation dominates the other sources of renewable power. However, integration of wind power system to the existing power system possess a number of problems in view of achieving good power quality, stability and power dispatching issues, due to the fact it is non-dispatchable and volatility. These problems can be resolved if one could forecast the wind speed and wind power. It may be noted that as wind power is a function of wind speed, forecasting of wind power can be accomplished though wind speed forecast. But wind power generation depends on the availability of the wind. It is estimated that by 2020, about 12% of the world's electricity will be available through wind generation [3].

The greatest problem in wind power penetration is due to the irregular nature of wind speed. There are several methods to estimate wind speed and wind power. These methods are classified into distinct groups namely the physical and statistical method of forecasting. Existing methods for wind power forecast takes numerical weather prediction (NWP) parameter as forecast input.

Simultaneous time and frequency information can be analyzed with wavelet transformation. Because of this property of wavelet transform technique a signal can be better analyzed with an irregular signal pieces. For a non-stationary signal it is essential to get information that how much of each frequency component exists at which time. This can be achieved with wavelet transformation analysis. In this part of the project, the time series data for wind speed is analyzed better with wavelet technique. The available wind speed sample (2982 sample) data collected from the National Renewable Energy Laboratory (NREL)[1] has been studied with different wavelet techniques (discrete wavelet technique and maximum overlap discrete wavelet technique) and because of no down sampling property of MODWT wavelet technique, wind speed sample can be better analyzed with maximum overlap discrete wavelet technique (MODWT). Available wind sample has been decomposed up to 5^{th} level with the help of MODWT. Each decomposed signals are forecasted individually with three different neural networks (multilayer feed-forward neural network, wavelet based multilayer feed-forward neural network and recurrent wavelet neural network) and finally each level forecasted output sample are added to get wind speed forecast up to 30 hours ahead. Because of neural network's capability to map non-linear relationships of input-output patterns, here in this thesis neural network has been chosen for wind speed forecast. The studied system is modeled and simulated in the MATLAB-Simulink environment.

1.2Literature Review on wavelet techniques and wind speed/power forecasting

There are several existing models for wind speed/wind power prediction. NWT (numerical weather prediction) models predict the weather not just the wind [5]. Persistence model for prediction problem is better than NWP model. Basically forecasting model divided into two approaches that is physical and statistical approaches. NWP model comes under the physical approaches of wind speed/wind power estimation where meteorological conditions are taken into account. In case of statistical approach amount of data taken for consideration should be more, where meteorological information does not require. Autoregressive (AR), moving average (MA), autoregressive moving average model (ARMA) and autoregressive integrated moving average model (ARIMA), all these models comes under statistical approach for forecasting problem. Learning approaches like neural network (NN), fuzzy logic, support vector machine (SVM), all these approaches learn from the relationship between predicted values and the historical time series. Neural network has been shown as better approximation capability than other models [6], [7], and [8]. In control application like in wind turbines control, wind forecast is carried out up to few seconds [9] and [10]. The wavelet technique for wind speed forecasting has been first introduced by Hunt and Nason. Short term wind data has been collected from a site and long term data from a reference site using Measure correlate predict technique, wind speed and power has been predicted. Accurate predictions of wind speed and power at 10-min intervals up to 1h into the future by the support vector machine regression algorithm provided in [11]. Integration of wind power system to existing one, an advanced statistical method has been developed where forecasting horizon will be 48h ahead [12]. An advanced model, based on recurrent high order neural networks, with forecast of the WECS power output profile for the next 2 or 3 hours with a time step in the order of 10-min [13].

ANN involves two steps: training or learning step and testing step. During training phase all free parameters get updated to model the given problem. After learning step, it may be tested with new unknown patterns of inputs and its accuracy can be tested during testing step. ANN has become a powerful computing technique because of its capability to map nonlinear relationships of input-output patterns. Complex valued pipelined recurrent neural network (CPRNN) architecture is proposed where the network is trained by the complex valued real-time recurrent learning (CRTRL) algorithm with a complex activation function which is suitable for forecasting wind signal in its complex form (speed and direction)[14]. A 2-day forecast is obtained by using novel wavelet recurrent neural networks (WRNNs) [16]. Three different forecast scenarios are simulated based on the persistence approach where a linear approximation has been developed to describe the relationship between the persistence forecast and the related mean measured power [17].An advanced model, based on recurrent high order neural networks, is developed for the prediction of the power output profile of a wind park [18]. A case study from Tasmania, Australia has been done with a short term wind prediction model for power generation where the approach model is the application of an *adaptive neuro-fuzzy inference system* to forecasting a wind time series [19].Some example of statistical model for wind power forecast, takes the NWP forecast as a inputs which has been proposed, involves forecasting models as the wind power prediction tool (WPPT), a time series-based statistical model, wind power management system (WPMS), and advanced wind power prediction system (AWPPS) are artificial intelligence and fuzzy-based models [20],[21].Wind power forecasting strategy developed where feature selection component and a forecasting engine has taken under consideration [22].A combining approach of wavelet transformation, particle swarm optimization process, and an adaptive-network-based fuzzy inference system is proposed for short-term wind power forecasting in Portugal [23].

1.3 Motivation

In recent years availability of power in India as well as worldwide has both increased and improved but demand has consistently overtaken the supply. Because of this, non-conventional sources like wind and solar have become the center of attraction. Among these, fastest growing area is the wind energy system. Now India has become fifth in installed capacity of wind power plant. As of 31st march the installed capacity of wind power in India was 17967MW [2].

Wind power system penetration to the existing power system possess problems as running problems (frequency, power balance, voltage support, and quality of power), planning and economic problems (including uncertainty in wind power in to unit commitment, economic load scheduling, and spinning reserve calculations), etc. [4].

1.4 Objectives of the Thesis

The objectives of this research work are as follows.

- To get a forecast model without NWP parameter as a forecast inputs, and with reasonable forecast up to minimum 2-3 months, to offer in the electricity markets.
- To have a comparison study between two wavelet techniques (DWT and MODWT) for better analysis of the wind speed sample which will be given to the forecast models .
- To have also a comparison study between three neural networks for wind speed estimation this can be further used for wind power system to integrate with existing power system.

1.5 Thesis organization

Organization of the thesis is as follows

CHAPTER1 describes the research motivation and thesis objectives.

CHAPTER2 describes the wavelet analysis over Fourier analysis and different types of wavelet transformation techniques.

CHAPTER3 include different types of neural networks (multilayer feed forward neural network, wavelet based multilayer feed forward neural network and recurrent wavelet neural network) to estimate wind speed with their results and discussion.

CHAPTER4 describes conclusions and future works.

CHAPTER 2

Wind Speed and Power Forecasting using Wavelet Techniques

2.1Wavelet Analysis over Fourier analysis

Wavelet transforms convert time series (here wind speed) into elementary forms at different positions and scales. These elementary forms of wind samples gives better behavior (means filtering effect) than the original wind speed series, and hence, they can be predicted more accurately. As Fourier transforms fails to analyze a non-stationary signal. The wavelet transform is a mathematical tool, much like a Fourier transform in analyzing a stationary signal that decomposes signal into different scales with different levels of resolution by dilating a single prototype function [24].One of the major difference between wavelet analysis and Fourier analysis is Fourier transform provides global representation of a signal but wavelet analysis gives local representation (in time and frequency) of the signal. FT (Fourier transformation) possess fixed window width.

Wavelet transformation is the forward transformation where the transformation process is from time domain to time scale domain. Like Fourier transform, WT divides a signal into small pieces. However, while Fourier transform uses regular sine waves, assumed to be of infinite length, of various frequencies, WT uses the scaled and offset forms of limited duration, irregular and asymmetric signal pieces, which is called the mother wavelet [25].A signal can be analyzed better with an irregular signal pieces.

Mathematical transformation of a signal is required for further information which are not available in raw signal. Fourier transformation as well as wavelet transformation both is reversible transform. The frequency information of a signal can be analyzed with Fourier transformation technique, that means how much of each frequency component exists in the signal, but it fail to analyzed about time, that means at which time these frequency components exist. Time domain analyses are not required when the signal is stationary. FT gives the spectral content of the signal, but it gives no information regarding where in time those spectral components appear. Therefore, FT is not a suitable technique for non-stationary signal. WT is the time-frequency representation. Time and frequency analysis of a signal can well analyze through wavelet transformation (WT).

2.1.1 Some applications of wavelet transform

Wavelet is a statistical tool used in wide range of areas, such as

- Signal processing
- Data compression
- Fingerprint verification
- DNA, analysis
- Finance etc.

2.2Wavelet analysis

Wavelet transforms decomposes the original signal into several signals in different scales of resolution by multi-resolution (MRA) technique [26] where the original time domain-signal can be recovered without losing any information. One of the similarities between wavelet analysis and Fourier analysis is, wavelet analysis involves the projection of the original series into a sequence of basic functions, which are known as wavelets. The demerits of FT can be overcome by STFT (short time Fourier transform). But it (STFT) has also disadvantage as the window width is fixed.

The mathematical equation for MRA is

$$A_j = D_{j+1} \oplus A_{j+1} = D_{j+1} \oplus D_{j+2} \oplus ... \oplus D_{j+n} \oplus A_n \tag{1}$$

Where the approximation version of the signal at $j+1$is A_{j+1}, $D_{j+1}$is the detail version of the signal at scale $j+1$, $\oplus$is the addition of the decomposed signals, n is the level of decomposition. The father wavelet (called also a scaling function),φ and the mother wavelet (called also a wavelet function),ψ , are the two basic wavelet functions which can be scaled and translated.

The father and mother wavelets are defined by the functions:

$$\varphi_{j,k}(t) = 2^{-j/2} \varphi(2^{-j} t - k) \tag{2}$$

$$\psi_{j,k} = 2^{-j/2} \psi(2^{-j} t - k) \tag{3}$$

2.2.1 Continuous wavelet transforms (CWT)

From the Continuous Wavelet Transform (CWT), one can obtain the surface of the wavelet coefficients, for different values of scaling and translation factors which maps a function of a continuous variable into a function of two continuous variables.

In wavelet analysis, the input signal is compared with the wavelet function to obtain a set of coefficients that represent how these two signals match. The computation of these coefficients is performed using the continuous WT (CWT).

The definition of CWT for a given signal $x(t)$ with respect to a mother wavelet $\psi(t)$ is given by

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi(\frac{t-b}{a})dt \tag{4}$$

where b is the translation factor and defines the decomposition filters at different frequency levels and a is the scaling parameter and scales decomposition filters for each levels.

2.2.2 Discrete wavelet transforms (DWT)

A fast DWT algorithm based on the four filters (decomposition low-pass, decomposition high-pass, reconstruction low-pass and reconstruction high-pass) was developed by Mallat[27]. DWT is the digital representation of CWT which decomposes a discretized signal into different resolution levels. Computational time can be reduced with discrete wavelet transformation. In DWT the signal which is decomposed, its length is halved every time while passing through the filter pair leaving the signal with the signal length of $1/2, 1/4, 1/8, ...$ the original signal at level 1, 2, 3…etc. DWT is applicable for discrete time series signals. Instead of $a = a_O^m$, $b = nb_O a_O^m$. DWT of a discrete signal $f[n]$ is given as

$$DWT(m,l) = \frac{1}{\sqrt{a_O{}^m}} \sum_n f[n] g[\frac{l - nb_O a_O{}^m}{a_O^m}] \tag{5}$$

where g is the mother wavelet, l is the sample values.

One of the disadvantage of discrete wavelet transformation (DWT) is on length of the time series which must be power of 2.To obtain the jth level wavelet (detail) and scaling (smooth) coefficients, we first apply the jth level filters to x_t (input data samples) to obtain the detail and approximation coefficients.

The detail and approximation (smooth) coefficients, defined as

$$W_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L_j - 1} h_{j,l} x_{t-l \bmod N} \text{ (Detail coefficients)} \tag{6}$$

$$V_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L_j - 1} g_{j,l} x_{t-l \bmod N} \text{ (Smooth coefficients)} \tag{7}$$

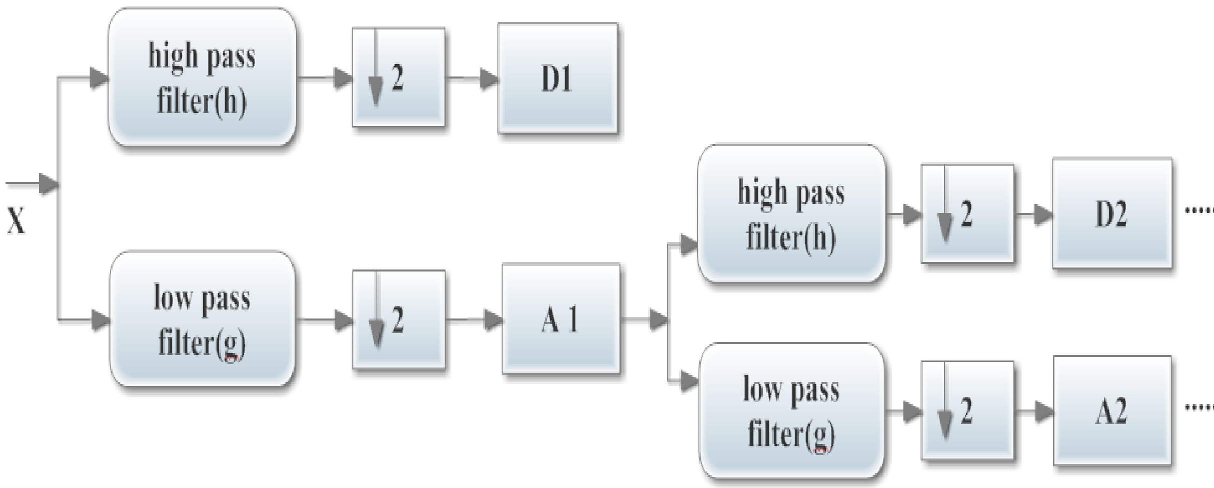

Fig.2.2.2 Decomposition of a signal(x) by DWT

Fig.2.2.2 shows the decomposition process of wind sample (x) with discrete wavelet technique where 2 stands for down sampling of the wind sample. D1, D2… are the detail coefficients of each decomposition level.A1, A2… are the approximation coefficients of each decomposition level.

2.2.3Maximum overlap discrete wavelet transforms (MODWT)

Multi-resolution analysis (MRA) of the given wind speed sample can be performed using maximum overlap discrete wavelet transformation (MODWT) which is based on filtering operations (Fig.2.2.3) known as 'Pyramid Algorithm' .

Pyramid Algorithm:

The original signal passing through high pass filter and low pass filters results in detail and approximation coefficients. The approximation coefficients which are obtained in the 1st level of decomposition, further allowed to pass through the next level wavelet (high pass filter)and scaling filters (low pass filter) which gives the next level detail and approximation coefficients. This process is repeated up to the required level of decomposition [4].

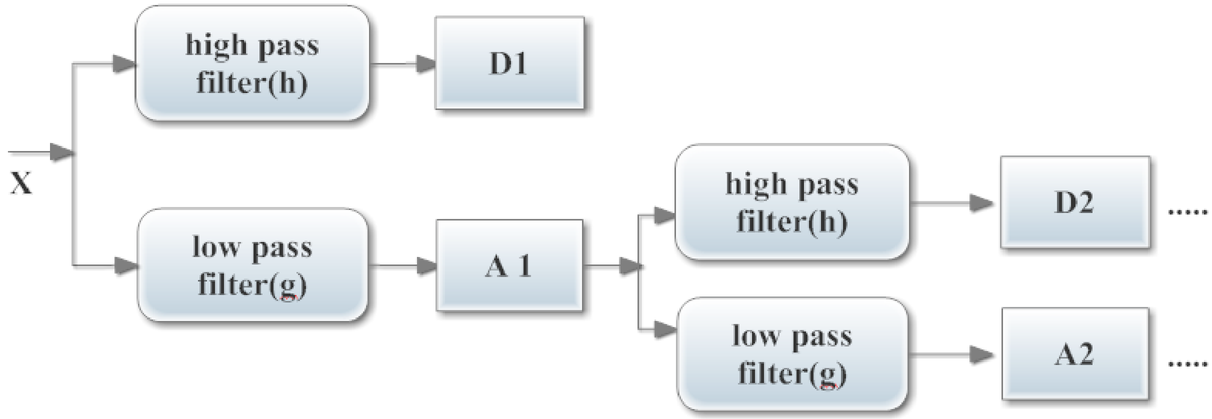

Fig.2.2.3 Decomposition of a signal(x) by MODWT

In Fig.2.2.3, X defines the input data samples (here wind speed), D1 and A1 are detail &smooth coefficients at 1st level of decomposition, D2 and A2 are details &smooth coefficients at 2ndlevel, etc.

In discrete domain, a signal defined as

$$X = \left[X_1, X_2, \ldots X_N \right]^T \tag{8}$$

where the length of the time series is N ($= 2^j$), then the DWT of X is given by [27],

$$W = \mathrm{O}X$$

where W is a column vector of length N whose nth element is the nth DWT coefficient W_n, and O is a $N \times N$ real valued matrix representing the DWT and satisfying orthonormal condition $\mathrm{O}^T\mathrm{O} = I_N$. Vector X can also be expressed as an addition of $j+1$ vectors of length N as

$$X = \mathrm{O}^T W = \sum_{j=1}^{J} \mathrm{O}_j^T W_j + v_J^T V_J = \sum_{j=1}^{J} D_j + S_J \tag{9}$$

where the jth detail signal is defined by D_j and the last vector is referred as smooth signal S_J which leads to the multi-resolution analysis.

2.2.4 Difference between discrete wavelet transform (DWT) and maximum overlap discrete wavelet transform (MODWT)

DWT

- DWT restricts the wind speed sample size to be a multiple of 2^j.
- DWT coefficients are associated with phase shifting filters.
- It is orthogonal transform.
- Circular shifting of time series is not possible. It is sensitive to where we 'break into' a time series.
- The number of wavelet and scaling coefficients N_j decreases by a factor of 2 for each increasing level of the decomposition.

MODWT

- There is no restriction to the sample size (wind speed). It is well defined for any sample size N.
- The MODWT details and approximations are associated with zero phase filters, thus making it easy to line up features in an MRA with the original time series [4].
- It is highly redundant, non-orthogonal transform.
- Circular shifting is possible.
- There is no down sampling occur in increase to the each level of decomposition.

2.2.4.1 Comparative study of wind speed with the two wavelet techniques

2982 numbers of wind speed samples are collected from National Renewable Energy Laboratory (NREL) [1]. Out of these 500 wind samples have been taken for wavelet analysis.

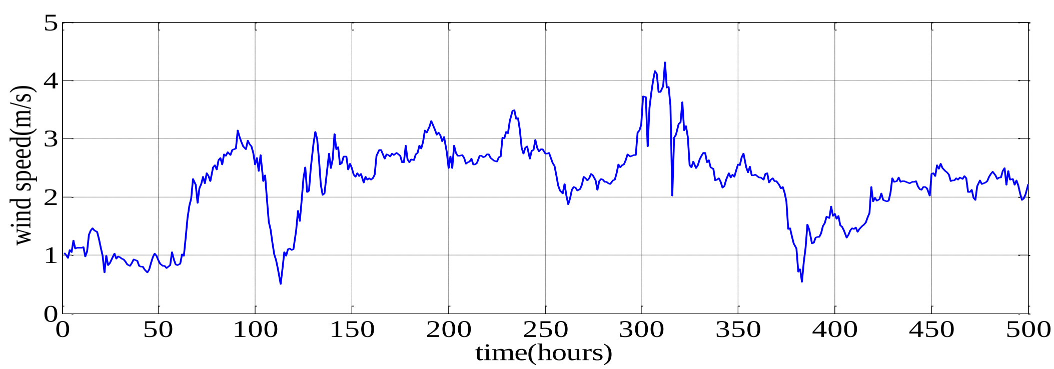

Fig.2.2.4.1 (a) Actual wind samples of consecutive hour ahead

In this project, 500 wind samples have taken for study with the two wavelet techniques (DWT and MODWT). And then each level decomposition detail and smooth coefficients are allowed to pass through three different forecasting models for wind speed forecasting.

Decomposition of wind samples by DWT

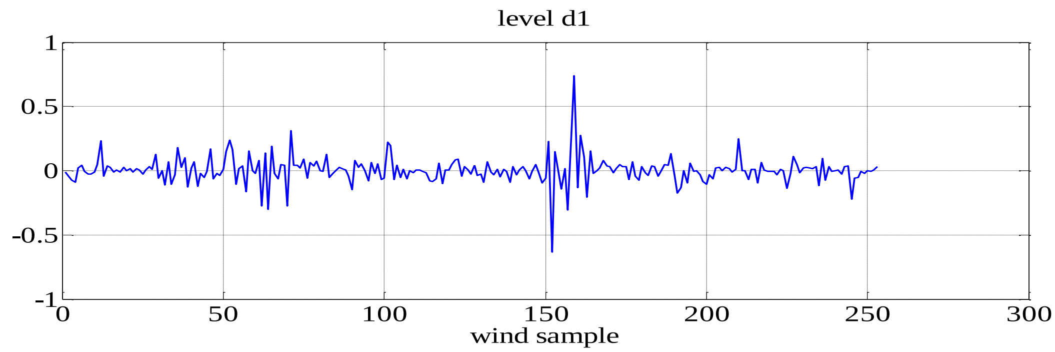

Fig.2.2.4.1 (b) Detail coefficients of 1st level decomposition by DWT

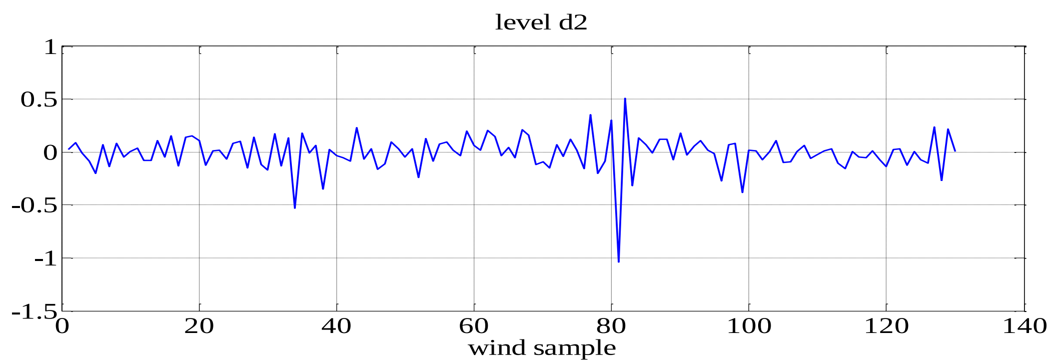

Fig.2.2.4.1(c) detail coefficients of 2nd level decomposition by DWT

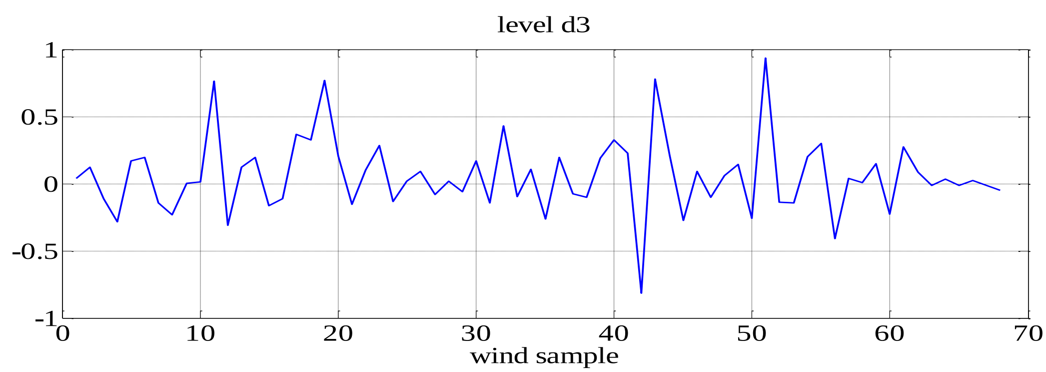

Fig.2.2.4.1(d) detail coefficients of 3rd level decomposition by DWT

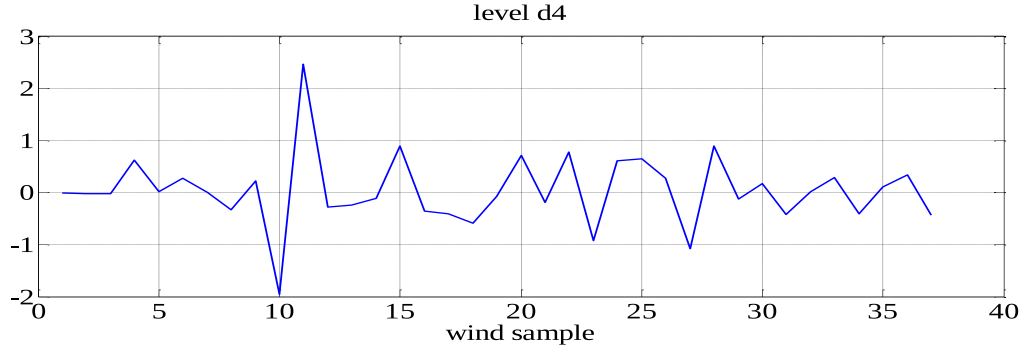

Fig.2.2.4.1(e) detail coefficients of 4th level decomposition by DWT

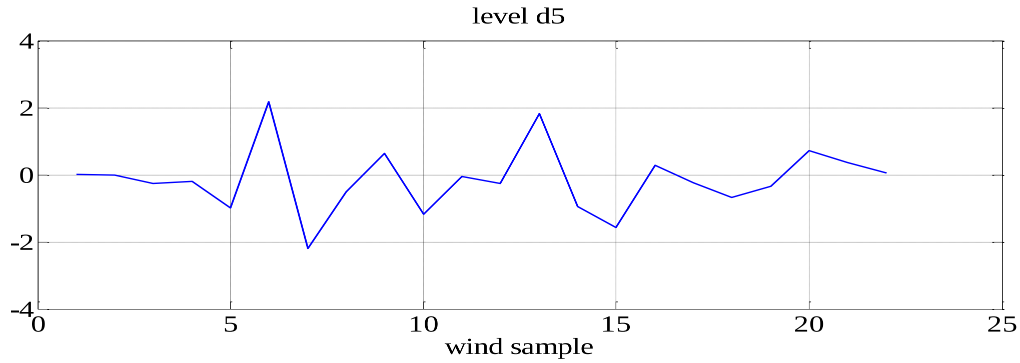

Fig.2.2.4.1(f) detail coefficients of 5th level decomposition by DWT

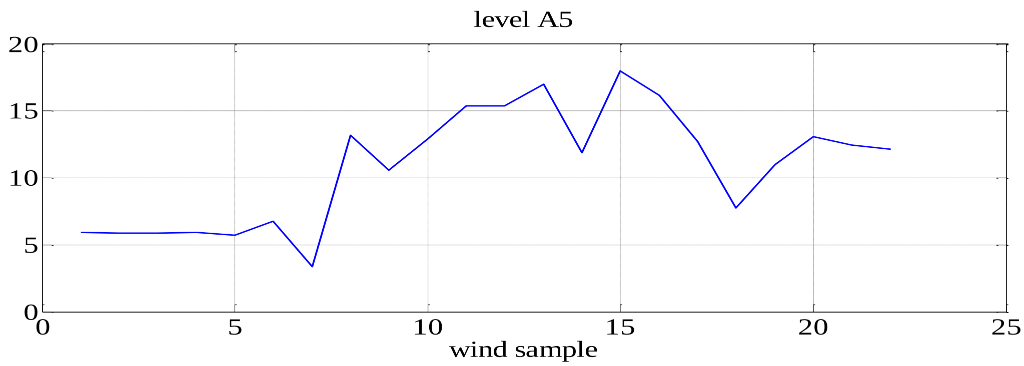

Fig.2.2.4.1 (g) smooth coefficients of 5th level decomposition by DWT

From Fig.2.2.4.1(b)-(g) show how the wind speed samples (detail and smooth coefficients of each level) are down sampled with a factor of 2, in each level of decomposition process carried out with discrete wavelet transformation technique (DWT) which results in reduction of data as well as may cause of loss of information of actual wind samples.

Decomposition of wind samples by maximum overlap discrete wavelet technique (MODWT):

500 numbers of wind speed samples are used to decompose with maximum overlap discrete wavelet technique

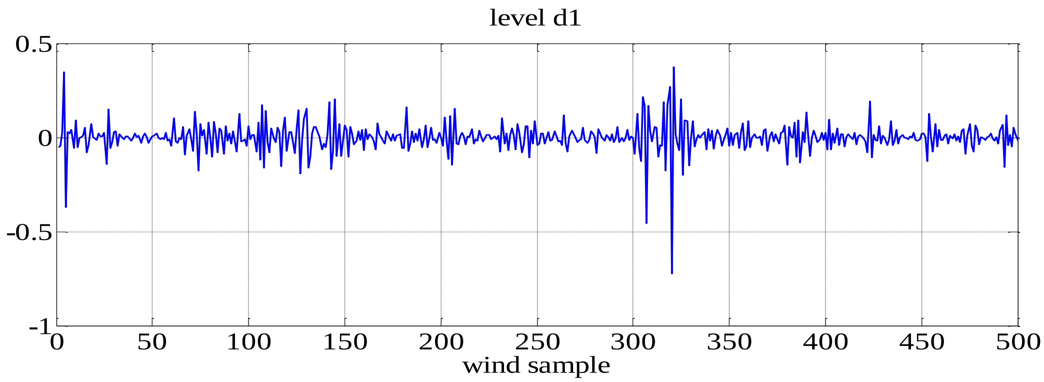

Fig.2.2.4.1 (h) Detail coefficients of 1st level decomposition by MODWT

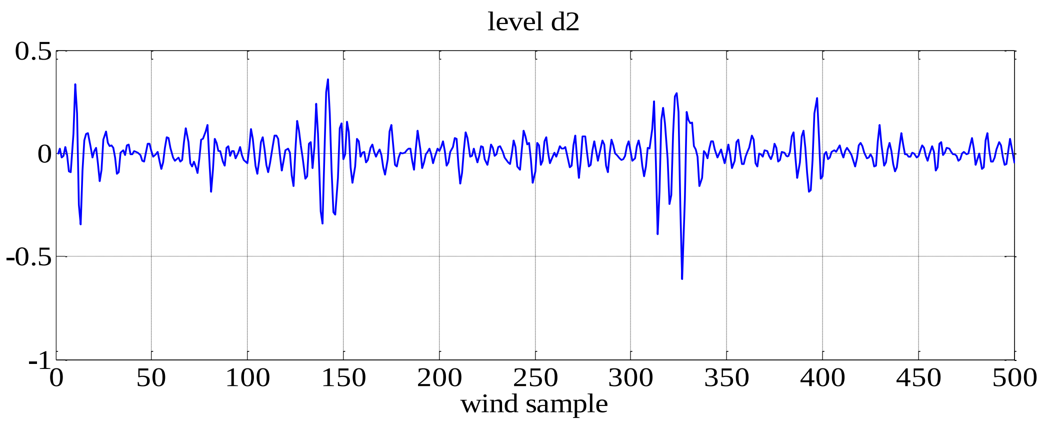

Fig.2.2.4.1 (i) Detail coefficients of 2nd level decomposition by MODWT

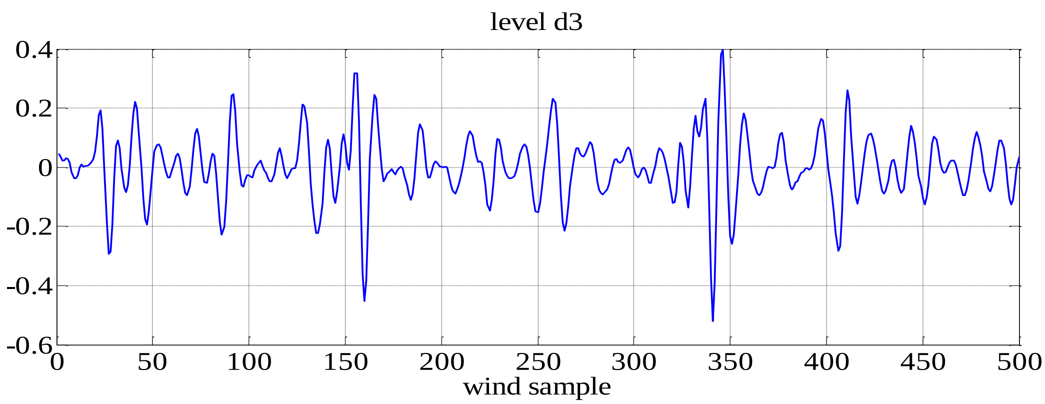

Fig.2.2.4.1 (j) Detail coefficients of 3rd level decomposition by MODWT

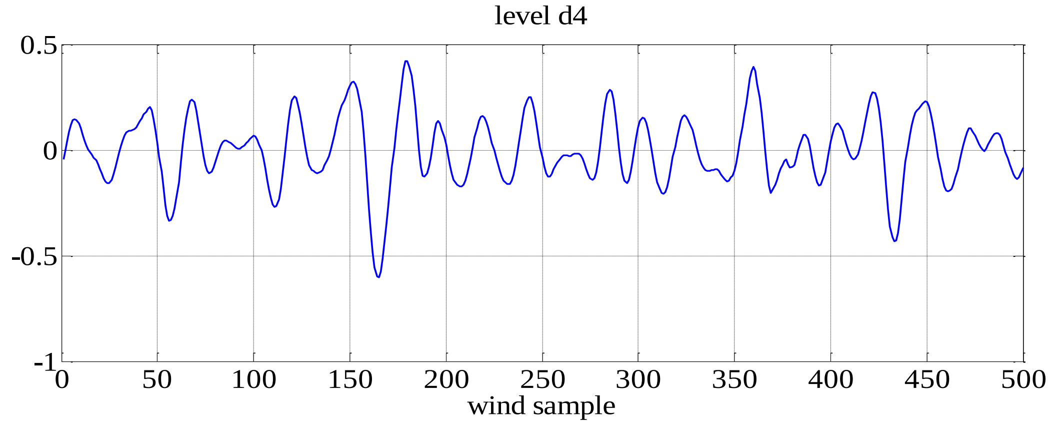

Fig.2.2.4.1 (k) detail coefficients of 4th level decomposition by MODWT

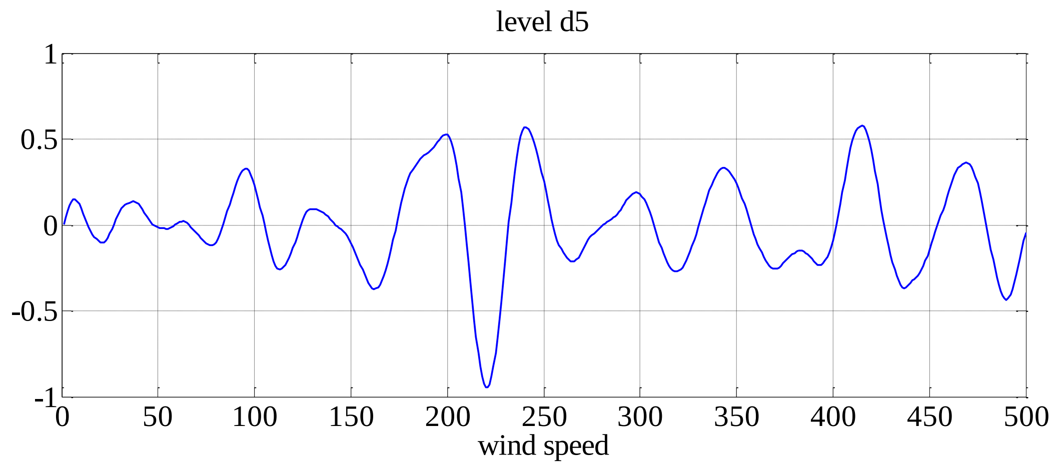

Fig.2.2.4.1 (l) detail coefficients of 5th level decomposition by MODWT

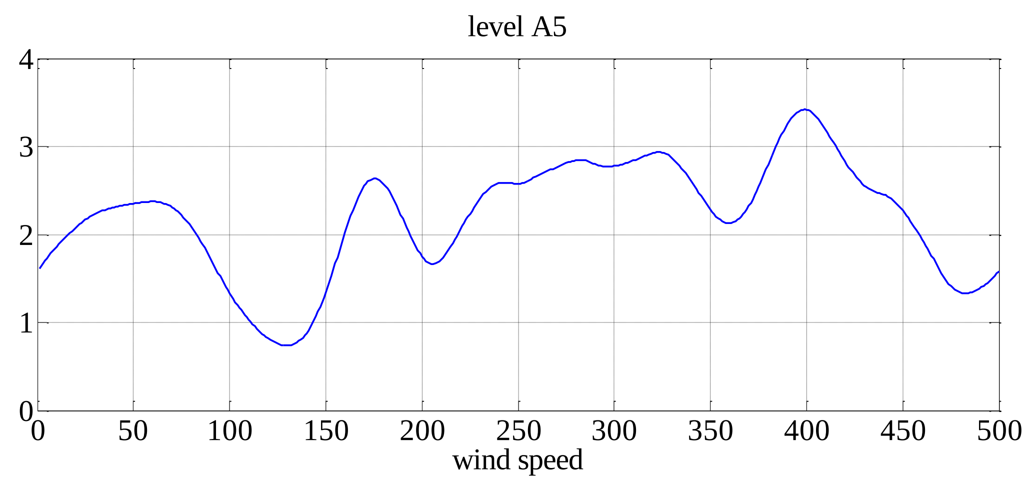

Fig.2.2.4.1 (m) smooth coefficients of 5th level decomposition by MODWT

Fig.2.2.4.1 (h)-(m) show the decomposition process of the MODWT (maximum overlap discrete wavelet transform).There is no down sampling of the wind speed sample occur in case of MODWT.

2.2.4.2 ACF of wind speed data with both the wavelet techniques

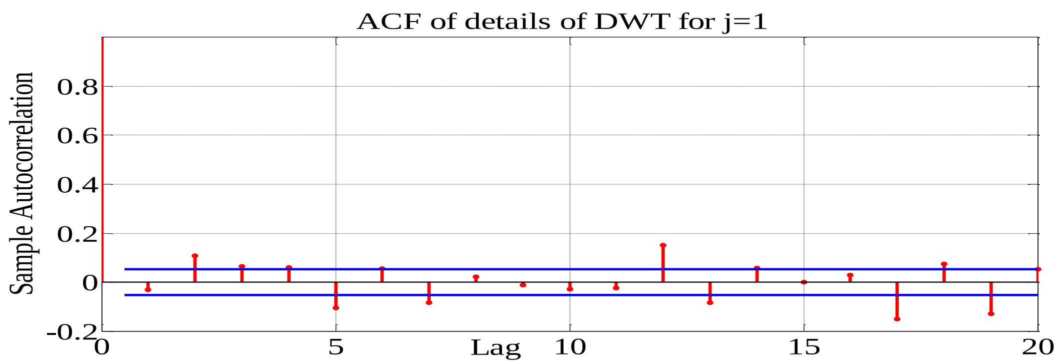

Fig.2.2.4.2 (a) ACF of wind speed data with 1st level decomposition by DWT

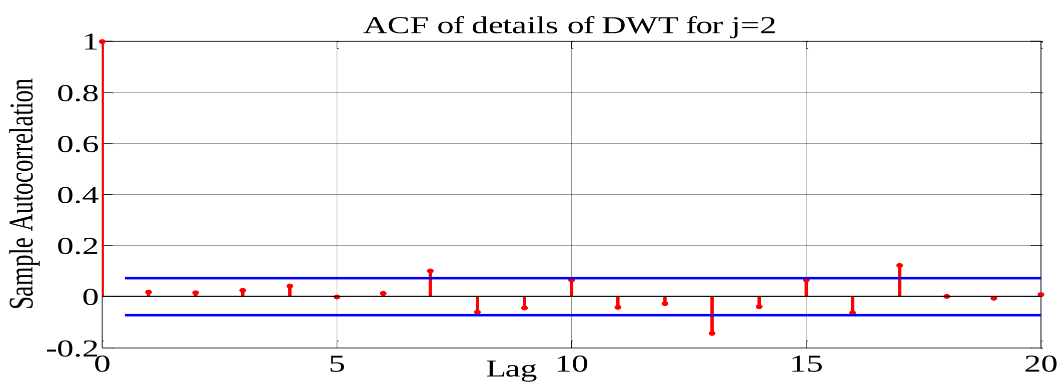

Fig.2.2.4.2 (b) ACF of wind speed data with 2nd level decomposition by DWT

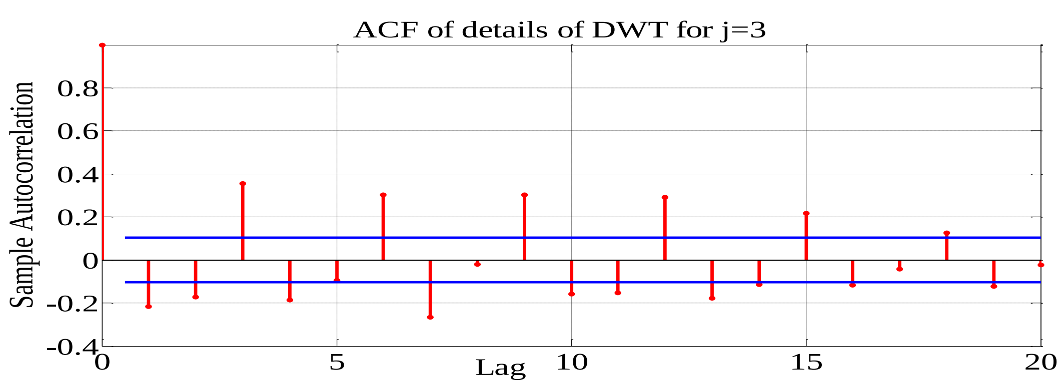

Fig.2.2.4.2 (c) ACF of wind speed data with 3rd level decomposition by DWT

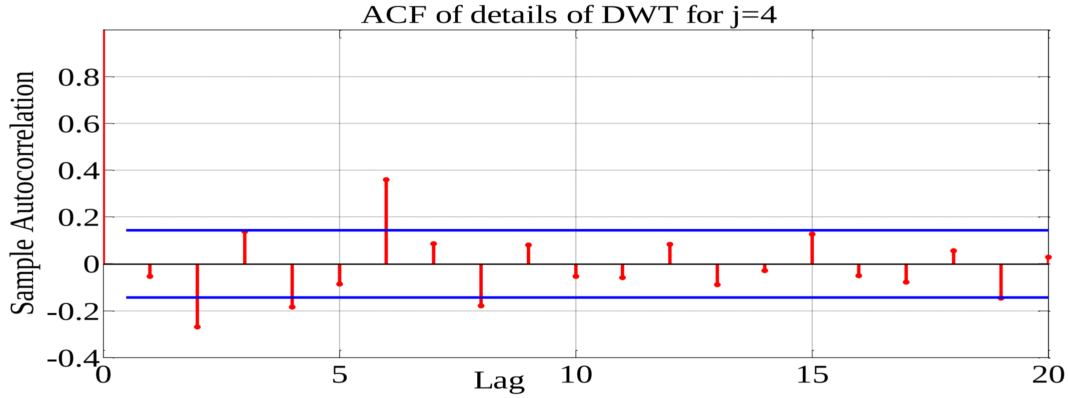

Fig.2.2.4.2 (d) ACF of wind speed data with 4th level decomposition by DWT

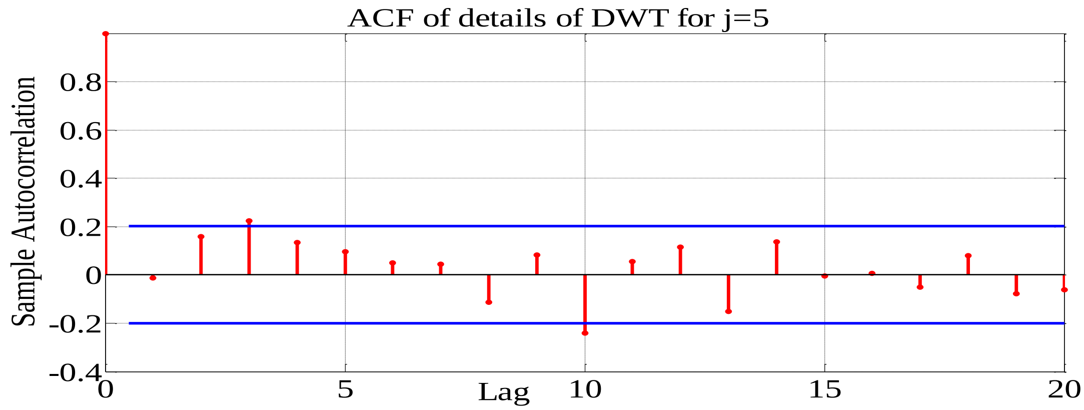

Fig.2.2.4.2 (e) ACF of wind speed data with 5th level decomposition by DWT

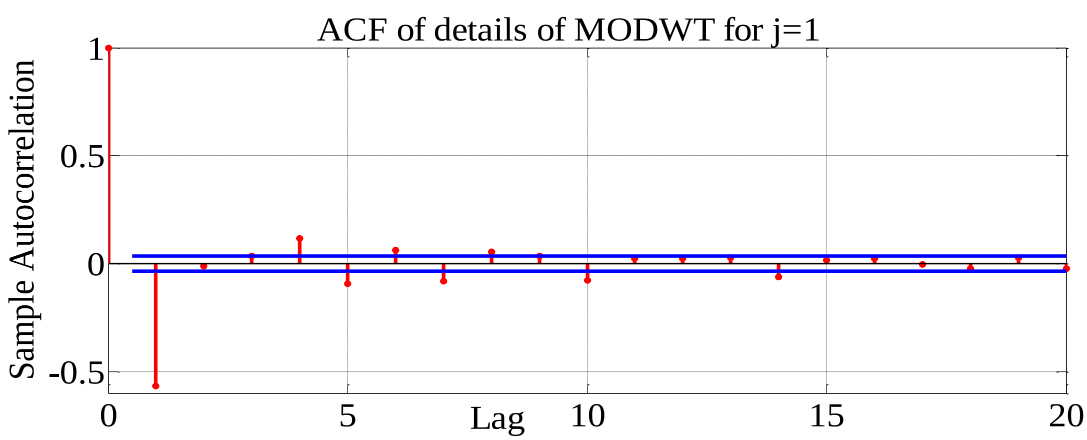

Fig.2.2.4.2 (f) ACF of wind speed data with 1st level decomposition by MODWT

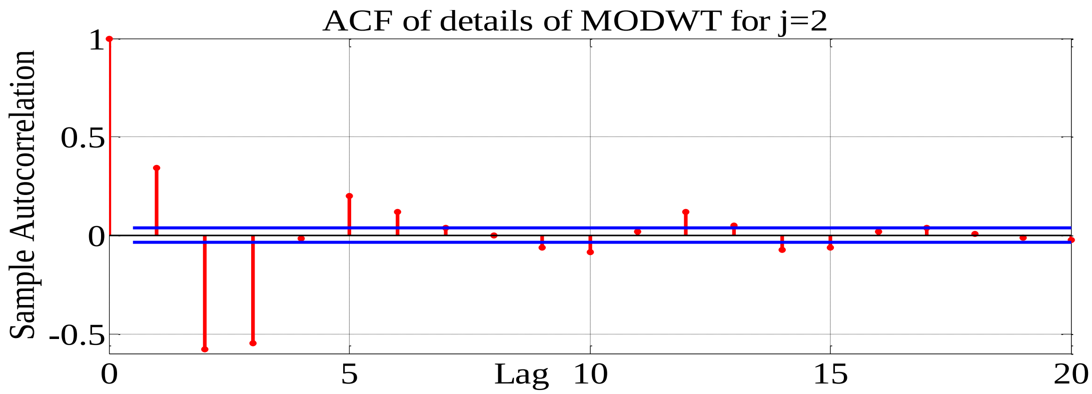

Fig.2.2.4.2 (g) ACF of wind speed data with 2nd level decomposition by MODWT

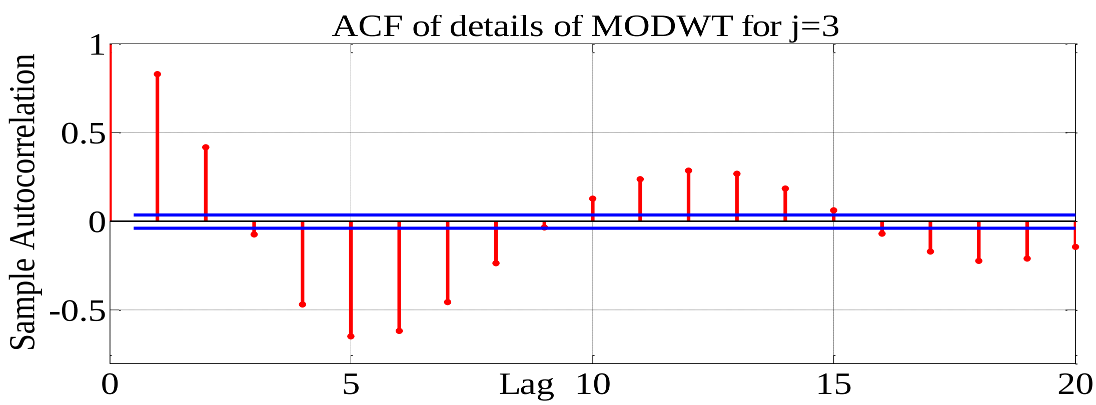

Fig.2.2.4.2 (h) ACF of wind speed data with 3rd level decomposition by MODWT

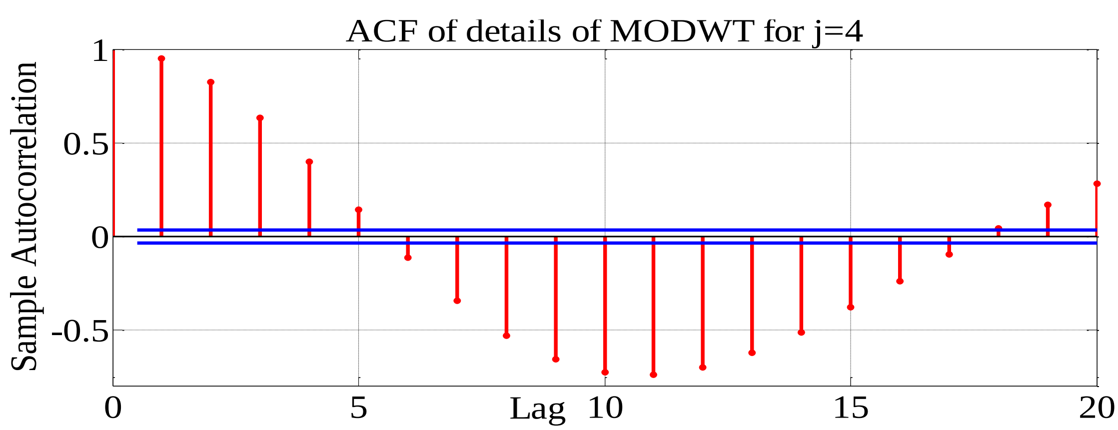

Fig.2.2.4.2 (i) ACF of wind speed data with 4th level decomposition by MODWT

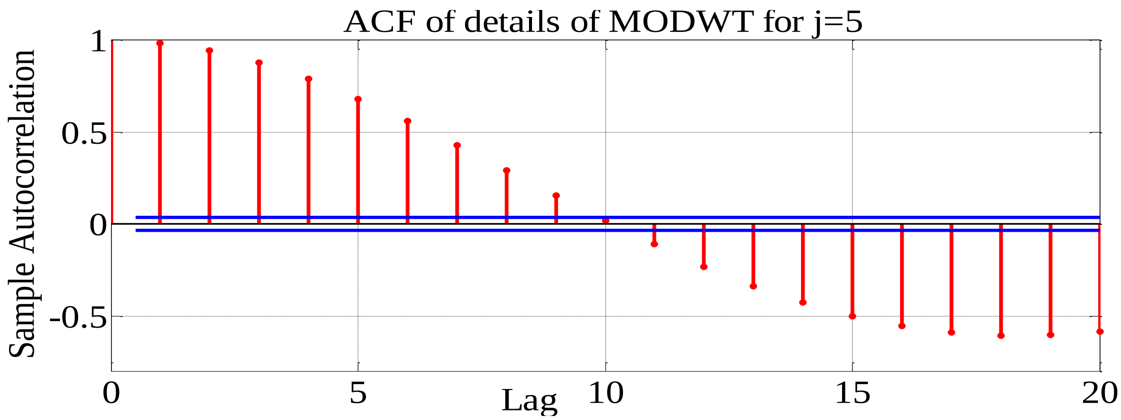

Fig.2.2.4.2 (j) ACF of wind speed data with 5th level decomposition by MODWT

2.2.4.3 Chapter Summary

From Fig.2.2.4.1 (b)-(m), decomposition results of both the wavelet techniques, it has been found that in DWT (discrete wavelet technique) wavelet technique in each level of decomposition, wind speed samples decreases by a factor of 2, so there may the possibility of loss of some important information but there is no down sampling occurs in MODWT (maximum overlap discrete wavelet technique). From Fig.2.2.4.2 (a)-(j) ACF (autocorrelation function) of wind speed up to 20 lag hours with both the wavelet techniques (DWT and MODWT). It has been clear that available wind series data can be best studied with MODWT wavelet technique as the ACF of each level all most all data with DWT lies within the performance index band. Hence wind speed prediction can give better results with MODWT wavelet technique.

CHAPTER 3

Wind speed forecast with three different neural networks

3.1 Wind speed estimation using BPA in multilayer feed-forward neural network

A back propagation networks consists of at least three layers that input layer, hidden layer and the output layer [29, 30]. The need of forecasting of wind speed is for errorless wind speed forecast results in accurate prediction on wind power which gives estimation of the expected production of wind turbines. Existing problem like operational, planning and economic problems which are created due to penetration of wind power system with the existing power system can be reduced. ANN consists of interconnected parallel distributed processor which have natural tendency for storing experimental data and making it available for use. BPA can be used to train this artificial neural network (ANN).Training has to begin with arbitrary weights.

Error= $[T-Y]^2$, T =Target output, Y =Actual output (10)

This neural network consists of three layers that are input layer, hidden layer and output layer. Here sigmoid function is chosen for activation function in hidden layer. Sigmoid function is define as

$$\phi(x)=\frac{1}{1+e^{-x}} \tag{11}$$

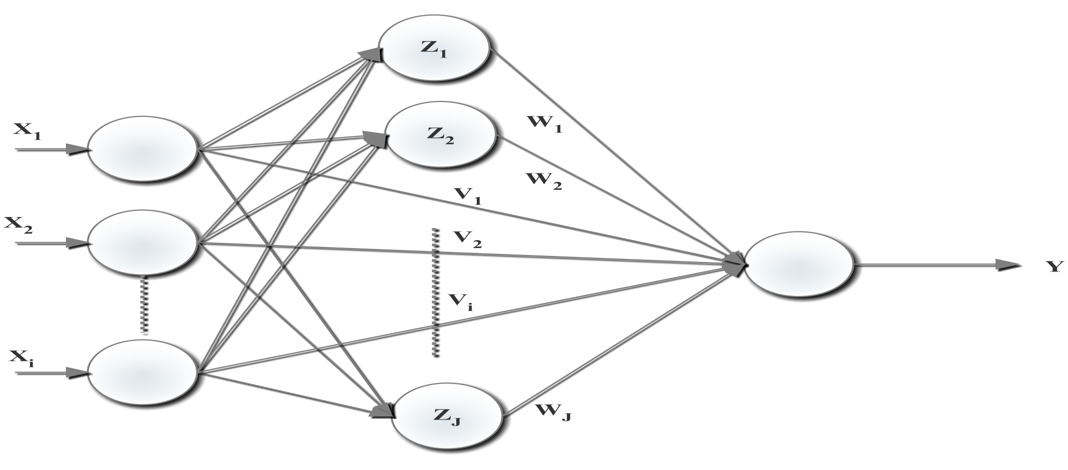

Fig.3.1 General Structure of multilayer feed forward neural network

Where $[X_1, X_2, ..., X_i]$ are the patterns given as input to the forecasting model, $[Z_1, Z_2, ..., Z_J]$ are the output of the hidden layer, $W_1, W_2, ...W_J$ are the weights connecting to output layer from hidden layer, $V_1, V_2, ..., V_i$ are the weights connecting to output layer from input layer. i Is the total number of input nodes and j as the number of hidden nodes, and finally Y as the total output of the forecasting model. For this model output can be computed as

$$Y = \sum_{n=1}^{i} X_n V_n + \sum_{m=1}^{j} Z_m W_m \tag{12}$$

3.2 Algorithm of multilayer feed-forward neural network for wind speed estimation

Algorithm 1(multilayer feed-forward neural network)
Step1.Normalized wind speed samples have been selected as input to the model. And normalization of the samples has been done by MODWT wavelet transforms with db4 mother wavelet. Decomposition of the wind speed samples (500) has been made up to 5th levels. *Step2. Each decomposed signal is allowed to pass through the forecasting model. And each level forecast has been done. Random weights are selected for initialization between hidden to output layer and input to output layer.* *Step3. For training step, first 10 wind speed samples (one pattern) are selected. 30 patterns have been considered for training.* *Step4. There will be no weights connecting from input to hidden layer, output of the input node is directly given to the hidden layer, output of hidden layer and output of output layers are evaluated by using sigmoid activation function.* *Step5. First 1-10 wind speed samples (one pattern) are selected and target is 11thwind speed sample and error has been evaluated. This error has been used to update weights.* *Step6. Next 2-11 wind speed sample have been given as inputs to the network*

and 12th wind sample is the target.

Step7. Similarly train the network for next 30 patterns.

Step8. This process has been continued till convergence occurs.

Step9. Final weights are stored after convergence.

Step10. For testing the network model 41-50 wind samples are given as input and 51st is the output sample. The output is used recursively for forecast the wind speed.

TABLE 1 (Input variables selected for the forecasting model)

Series	Inputs	Architecture
S5	1-10	10-5-1
D5	1-10	10-5-1
D4	1-10	10-5-1
D3	1-10	10-5-1
D2	1-10	10-5-1
D1	1-10	10-5-1

3.3 Wind Speed Prediction by a Multilayer feed-forward neural network

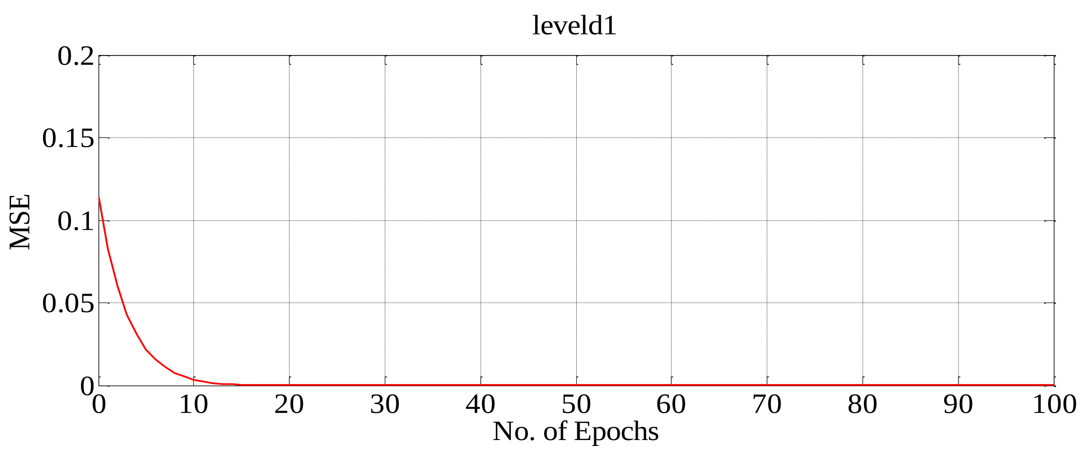

Fig.3.3 (a) mean square error for detail coefficients of 1st level

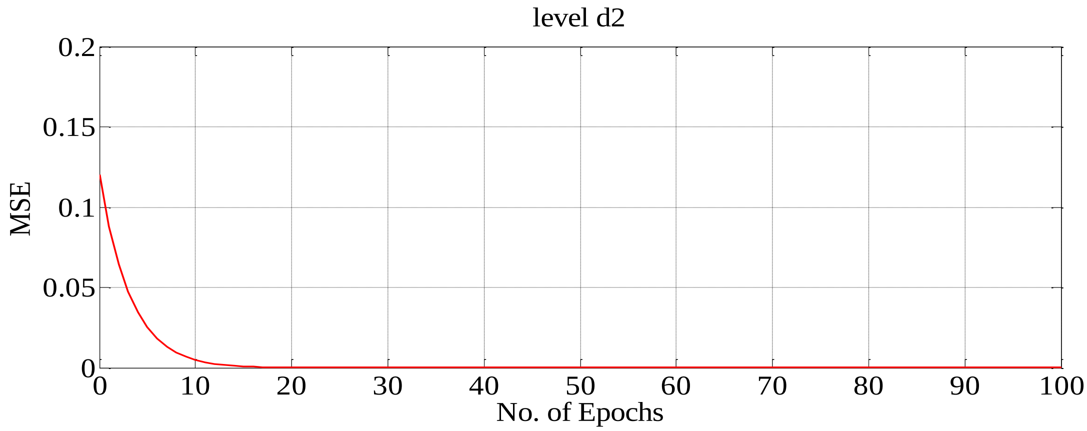

Fig.3.3 (b) mean square error for detail coefficients of 2nd level

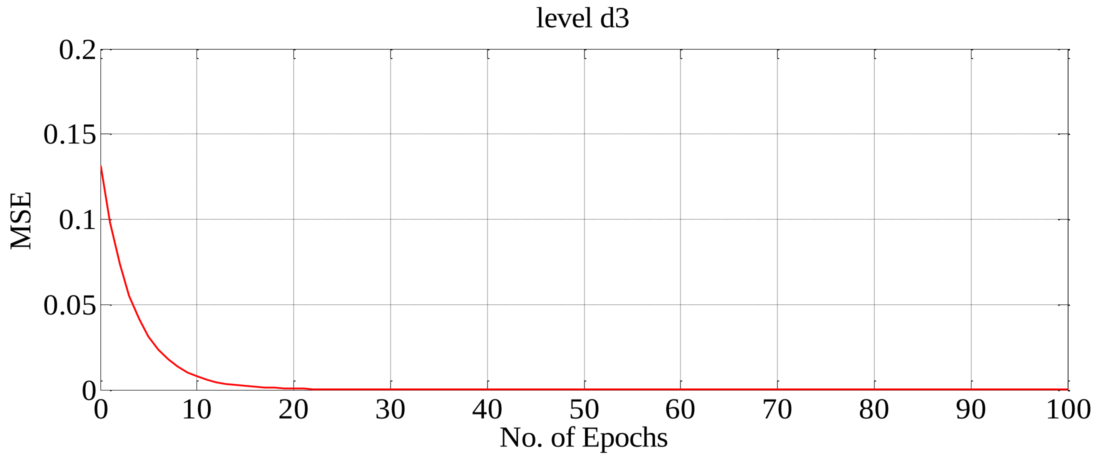

Fig.3.3(c) mean square error for detail coefficients of 3rd level

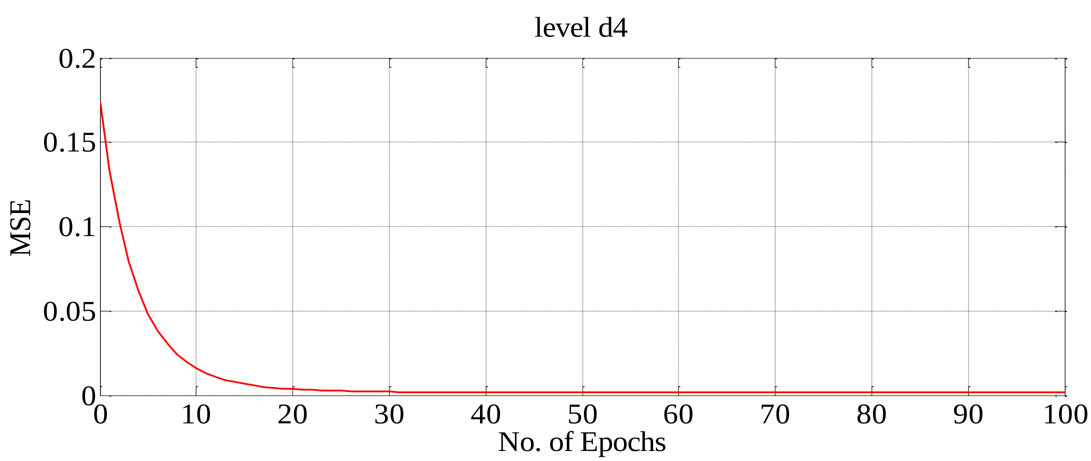

Fig.3.3 (d) mean square error for detail coefficients of 4th level

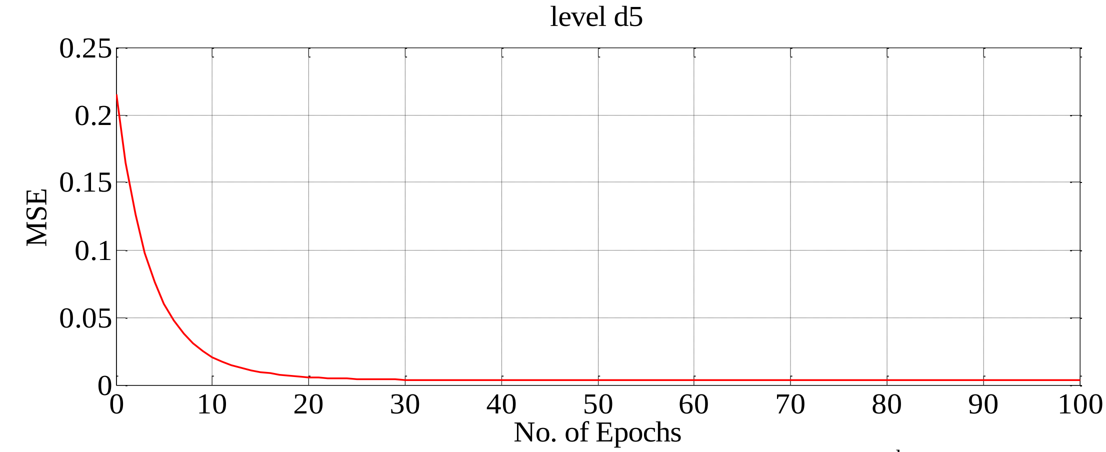

Fig.3.3 (e) mean square error for detail coefficients of 5th level

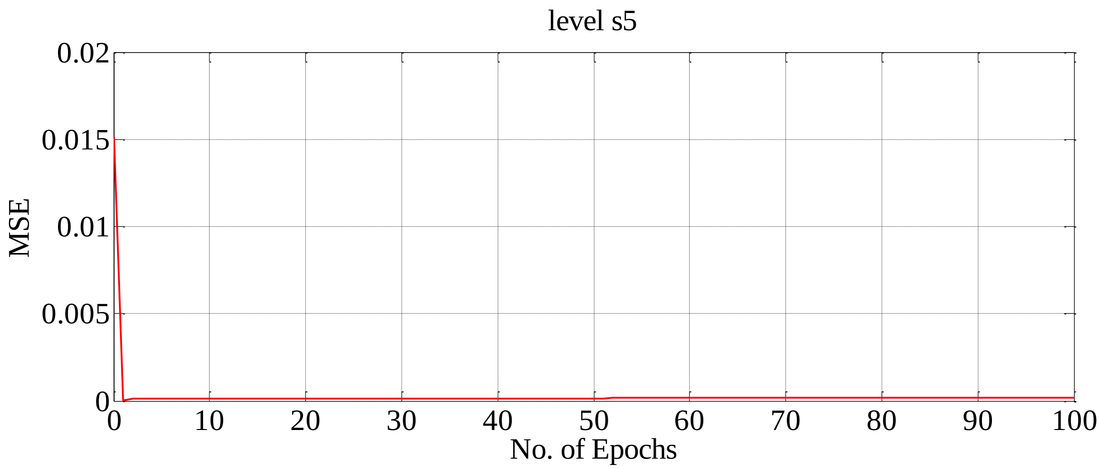

Fig.3.3 (f) mean square error for smooth coefficients of 5th level

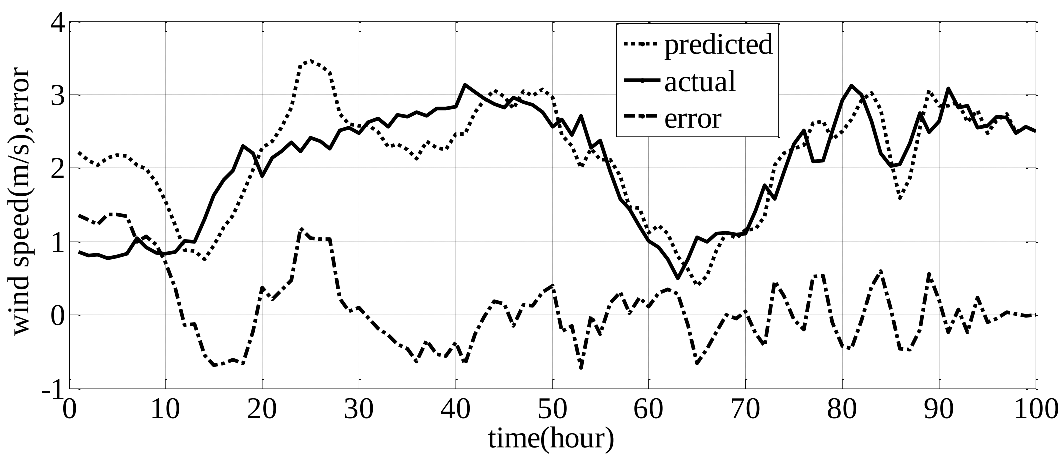

Fig.3.3 (g) wind speed forecasting of 100 look-ahead hour forecasting

3.3.1 Results and discussion

Estimation of wind speed up to 100 look-ahead with multilayer feed-forward neural network with sigmoidal activation function in hidden layer units shown in fig.3.3 (g) has an error around 10 percent. Hence that error of 10 percent can be reducing more with the help of wavelet neural networks (AWNN and RWNN). Performance index of this method for wind speed estimation can be calculated through mean absolute error (MAE), defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| = \frac{1}{n}\sum_{i=1}^{n}\left|e_i\right| \qquad (13)$$

where $\hat{y} =$ estimated wind speed through multilayer feed-forward neural network,

$y =$ Actual wind speed,

$n =$ Number of observation

And $e =$ error signal generated

Percentage of Mean absolute error (MAE) of wind speed estimation for the multi-layer feed-forward neural network model has been calculated from the fig.3.3 (g) as

$\%MAE = 10.1\%$.

3.4 Wind speed estimation by Artificial Wavelet neural network

Quick estimation can be possible by the WNN forecasting model with total five free parameters as input-to-output layer weights, hidden-to-output layer weights, bias, translation, and dilation. The AWNN offers better adaptivity as it uses wavelet coefficients instead of radial distances used in the RBFNN. As wavelets are localized functions, a fast initialization approach is employed in the proposed work to initialize the wavelet parameters that not only reduces the training time but also improves the accuracy. A linear relationship between input and output is mapped directly. A simple back propagation (BP) algorithm with adaptive learning rate is used for network parameter training. The forecasting scheme is as follows.

Algorithm2(wavelet feed-forward neural network)
Step1.Wavelet decomposition: The hourly wind speed data consisting of 1000 samples is decomposed to the 5th level using 'la8'.   Step2. Input pattern fed to the Wavelet Neural Network. The elements of each

pattern represent the values of continuous lag hours of available decomposed signal.

Step3.The function whose net area is zero can be the mother wavelet function. A Mexican hat is chosen as mother wavelet in wavelet layer (hidden layer).

Mother wavelet function $\psi(.)$ for the wavelet layer is defined as

$$\psi_{a,b}(u_i) = (1-(\frac{u_i - b}{a})^2) \times e^{-0.5((u_i-b)/a)^2}, i \in n; a,b \in \Re. \qquad (14)$$

where a is the dilation parameter and b is the translation parameter, i denotes the input nodes. Dilating and translating the mother wavelet over $\Re$ gives the discretized information instead of continuous one.

Input pattern for this neural network is defined as

$$u = \left[u_1\, u_2 \ldots\ldots u_n\right]^T \qquad (15)$$

where n denotes the number of input nodes. The input data in the input layer is directly passed to the wavelet layer.

$$Z_j = \prod_{i=1}^{n} \Psi_{a_{ij},b_{ij}}(u_i), j \in m. \qquad (16)$$

where Z_j is the output of wavelet layer (hidden layer), j is a integer value of hidden node units.

In order to map the linear input-output relation, it is customary to have additional direct connection from input layer to output layer, as there is no point in using wavelets for reconstructing linear term. The output of the AWNN, representing the hour-ahead forecast of the decomposed signal, can be computed as

$$y = \sum_{j=1}^{m} w_j z_j + \sum_{i=1}^{n} v_i u_i + g \qquad (17)$$

Step4. Wavelet Reconstruction: The signal is reconstructed using original and new predicted approximation & detail coefficients. The reconstructed signal contains the original samples plus 30 hours predicted wind speed data.

TABLE 2 (Input variables for this (WNN) forecasting models)

Series	Inputs	Architecture
S5	1-10	10-2-1
D5	1-10	10-2-1
D4	1-10	10-2-1
D3	1-10	10-2-1
D2	1-10	10-2-1
D1	1-10	10-2-1

Training Algorithm:

The back propagation gradient descent algorithm is used for training the wavelet neural network. Training is based on minimization of cost function that is mean square error (E) in this forecasting model.

Mean square error is given as

$$E = \frac{1}{2p}\sum_{k=1}^{p}[e(k)]^2 \tag{18}$$

where p is the total number of input pattern given to the forecasting model (to input layer) and the error signal generated from the forecasting model at each k^{th} input pattern is $e(k)$ which is defined as

$$e(k) = y^d(k) - y(k) \tag{19}$$

where $y(k)$ is the forecasted output and $y^d(k)$ is the desired output for a given k^{th} input pattern.

The updating of the free parameter is given as

$$\lambda(k+1) = \lambda(k) + \eta\Delta\lambda(k) + \alpha\Delta\lambda(k-1) \tag{20}$$

where λ is any unknown free variable, η and α represent learning and momentum parameter, respectively. All free parameters can be updated by

$$\Delta w_j = ez_j,\ j \in m \tag{21}$$

$$\Delta v_i = eu_i, i \in n \tag{22}$$

$$\Delta g = e \tag{23}$$

$$\Delta a_{ij} = \frac{ew_j z_j}{a_{ij}} [\frac{u_i - b_{ij}}{a_{ij}}]^2 \times [3 - [\frac{u_i - b_{ij}}{a_{ij}}]^2] e^{-0.5[(u_i - b_{ij})/a_{ij}]^2} \quad (24)$$

$$\Delta b_{ij} = \frac{ew_j z_j}{a_{ij}} [\frac{u_i - b_{ij}}{a_{ij}}] \times [3 - [\frac{u_i - b_{ij}}{a_{ij}}]^2] e^{-0.5[(u_i - b_{ij})/a_{ij}]^2} \quad (25)$$

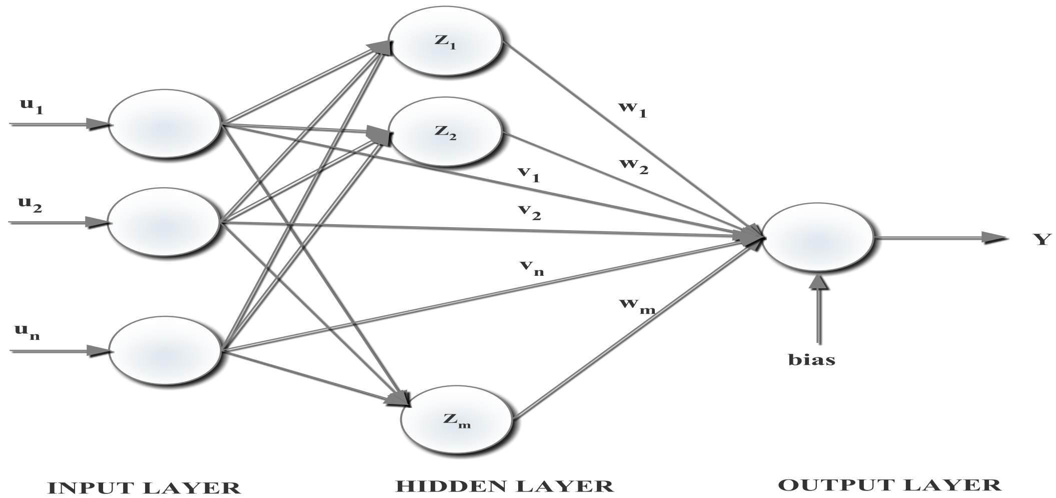

Fig.3.4 General Structure of wavelet neural network.

where $[u_1, u_2, ..., u_n]$ are the input patterns to the above neural network model, $Z_1, Z_2, ..., Z_m$ are the outputs of the hidden layer, $w_1, w_2, ..., w_m$ are the weights connecting to output node from hidden layer units, $v_1, v_2, ..., v_n$ are the weights connecting to output node from the input layer units and Y as the output of the forecast model.

3.4.1 Wind speed estimation with wavelet based multilayer neural network

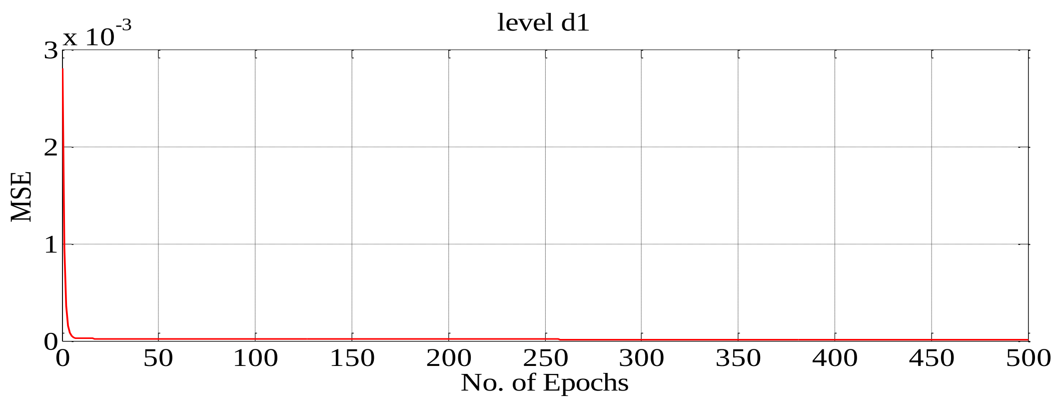

Fig.3.4.1 (a) mean square error for detail coefficients of level 1st

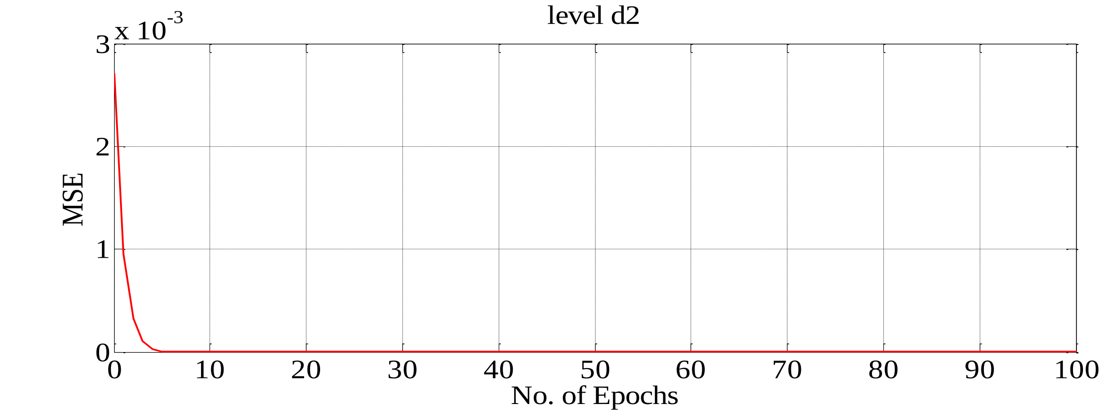

Fig.3.4.1 (b) mean square error for detail coefficients of level 2^{nd}

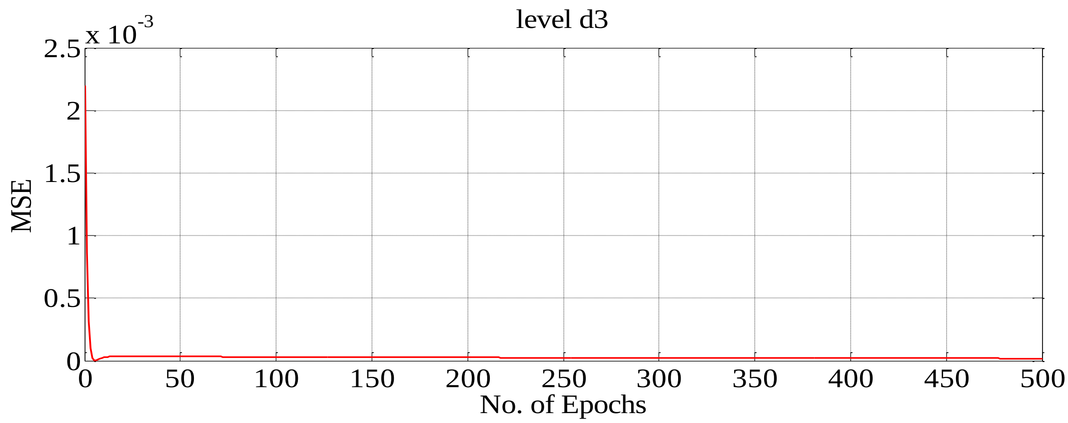

Fig.3.4.1 (c) mean square error for detail coefficients of level 3^{rd}

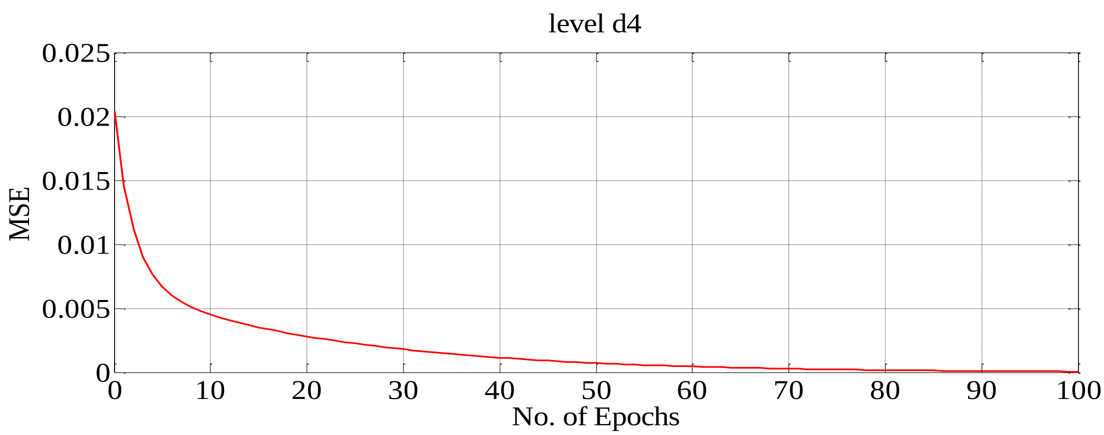

Fig.3.4.1 (d) mean square error for detail coefficients of level 4^{th}

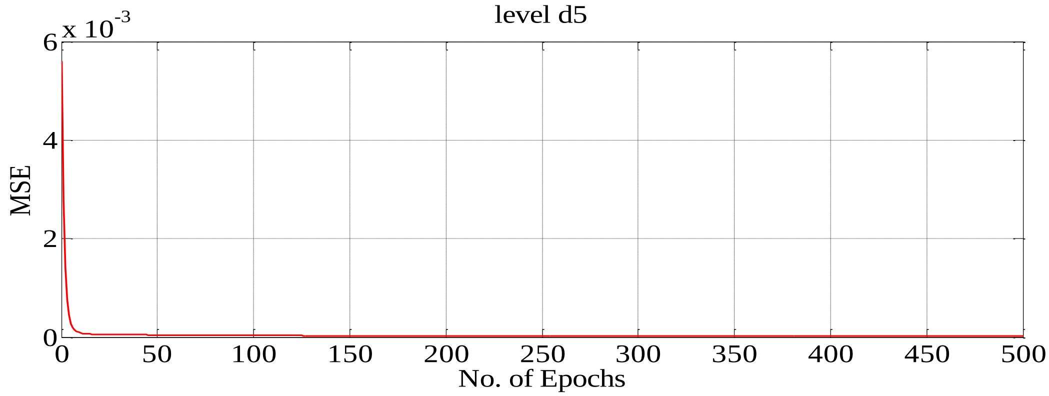

Fig.3.4.1 (e) mean square error for detail coefficients of level 5th

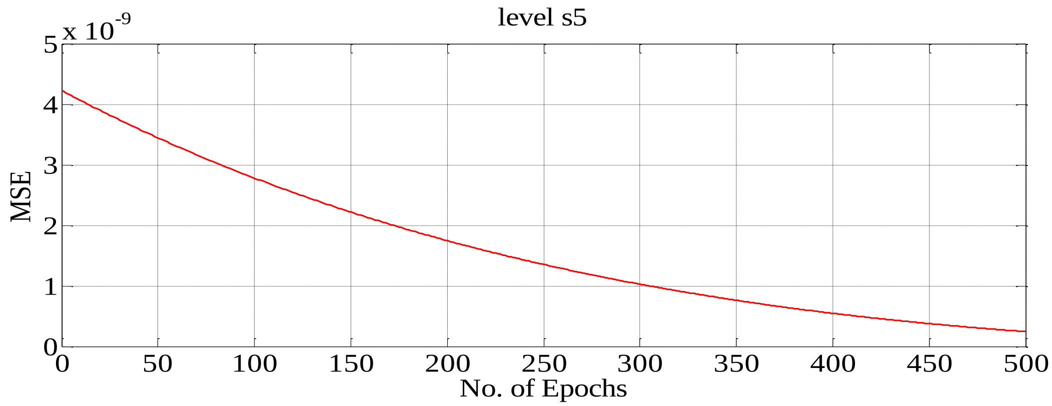

Fig.3.4.1 (f) mean square error for smooth coefficients of level 5th

Each level decomposed sample (detail and smooth coefficients) are allowed to pass through wavelet neural network for wind speed estimation and from Fig.3.4.1 (a)-(f), mean square error of each level coefficients shows faster convergence of the parameters than multilayer neural network.

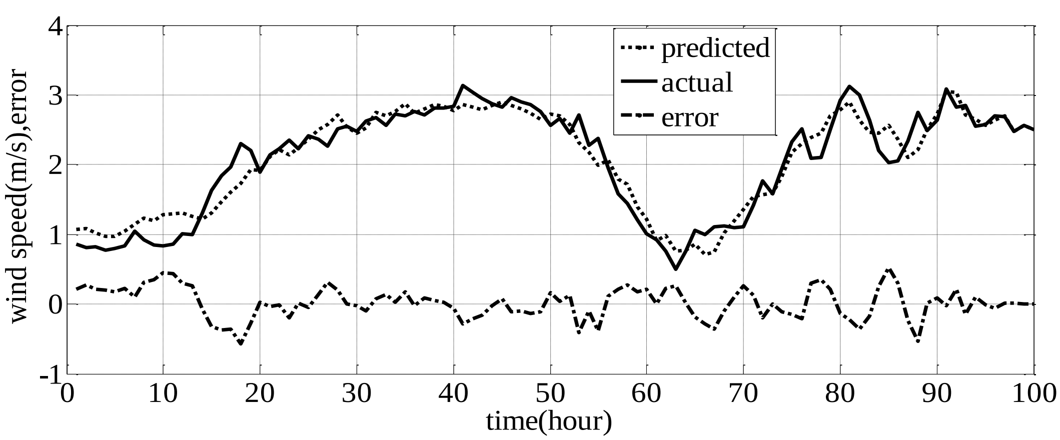

Fig.3.4.1 (g) wind speed forecast of 100 successive hour ahead forecasting with AWNN

3.4.2 Results and discussion

The above results of wind speed forecasting with AWNN shows better results than multilayer feed-forward neural network having activation function of sigmoidal type. The error is reduced to almost half as compared to multilayer feed forward neural network which is shown in Fig.3.4.1 (g). The effectiveness of this forecasting model has been studied with the mean square error (from Fig.3.4.1 (a)-(f)) of each level decomposed signal. Performance index of this method for wind speed estimation can be calculated through mean absolute error (MAE) which is same as eq. (13), defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| = \frac{1}{n}\sum_{i=1}^{n}\left|e_i\right|$$

where $\hat{y} =$ estimated wind speed through multilayer feed-forward neural network,

$y =$ Actual wind speed,

$n =$ Number of observation

And $e =$ error signal generated

Percentage of Mean absolute error (MAE) of wind speed estimation for the multi-layer feed-forward wavelet neural network model has been calculated from the Fig.3.4.1 (g) as

$\%MAE = 1.53\%$.

3.5 Wind speed estimation by recurrent wavelet neural network

Here the use of the wavelet RNN (WRNN) architecture to find a forecasting model for the prediction of wind speed is investigated. The main objective of this paper is to investigate the WRNN architecture for modeling and prediction of the wind speed. First we decompose the wind sample data sequence into several components (levels) of various time-frequency domains according to wavelet analysis. Next we use WRNN to make forecasts for all decomposed levels individually. Finally, the algebraic sum of all forecasts levels gives rise to final forecast samples.

WRNN algorithm:

This is achieved by feeding the network with a delayed version of the past observations. This network consists of three layers as the input layer, the hidden layer (input and context layers) and the output layer. The input layer units at time k receive as input not only the input vectors for time k but also hidden layer output of time k-1. The new inputs that are the feedback hidden layer outputs are called context vectors.

$$\psi_i(k) = f(x_d^{(1)}(k) + \sum_i \psi_i(k-1) \qquad (26)$$

where $\psi_i(k)$ is the output of hidden node j at time k, $f(.)$ is the hidden neuron function for the wind speed forecasting. And $x_d^{(1)}$ is the output of input layer at time k, $\psi(k-1)$ is output of the context layer.

Then the output functions $y(.)$ of the WRNN can be presented as follows:

$$y(n) = f_O(w_O + \sum_j w_j z_j(n)) + \sum_i v_i x_i \ , \qquad (27)$$

$$z_j(m) = \prod_{i=1}^{m} \psi_{ij} \qquad (28)$$

where $f_O(.)$ is the output neuron function of the output layer. w_O is the bias unit, w_j is the weights connecting the hidden unit j to the output unit, z_j is the total output from hidden layer. And v_i is the weight vector connecting from input layer unit to output layer unit.

The learning algorithm in the WRNN model is the same as that in the back propagation networks, using the gradient descent rule, which adjusts the weights based on the derivatives of the error with respect to the weights.

Mean square error (E) is used as a performance index for training the WRNN wind speed forecast model. For each time iteration, the error is back propagated to find gradients of errors for each weight and bias. The gradient is used to update the weights with the back-propagation training function. Here also training is based on minimization of the cost function. The mean square error (E) given as

$$E = \frac{1}{2N} \sum_{k=1}^{N} [e(k)]^2 \qquad (29)$$

And

$$e(k) = y^d(k) - y(k) \qquad (30)$$

where $y(k)$ is the forecasted output and $y^d(k)$ is the desired output for a given k^{th} input pattern. The updating of free parameter is same as in (19).

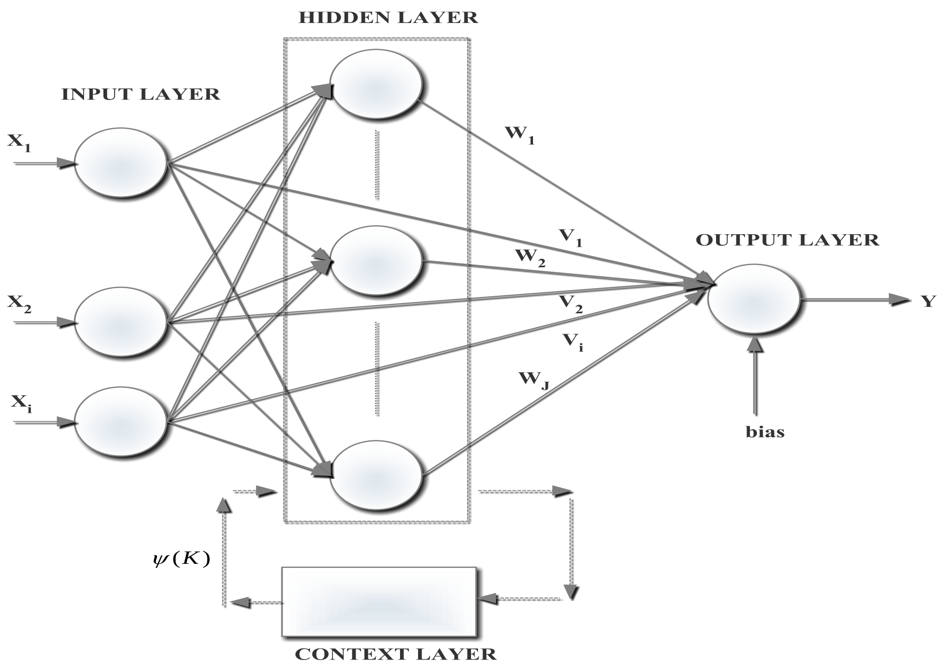

Fig.3.5 General Structure of WRNN (wavelet recurrent neural network)

TABLE 3(Input variables selected for this WRNN forecasting model)

Series	Inputs	Architecture
S5	1-10	10-2-1
D5	1-10	10-2-1
D4	1-10	10-2-1
D3	1-10	10-2-1
D2	1-10	10-2-1
D1	1-10	10-2-1

3.5.1 Wind speed estimation by wavelet based recurrent neural network

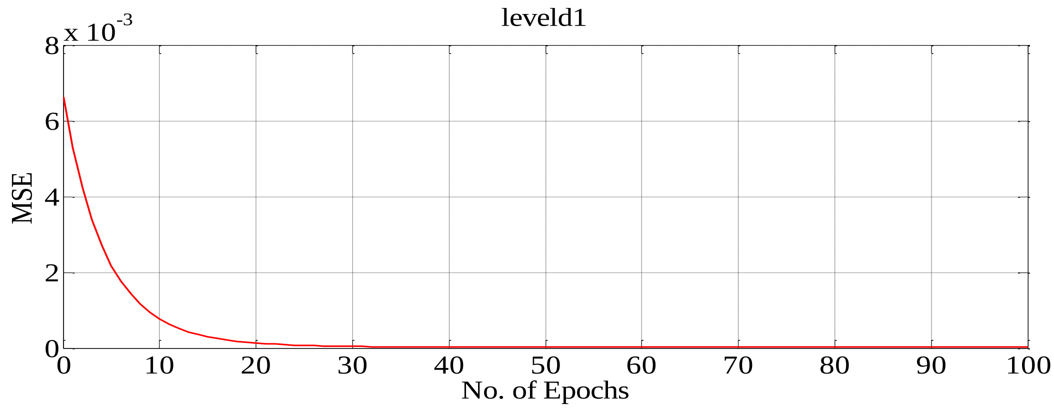

Fig.3.5.1 (a) mean square error for detail coefficients of level 1st

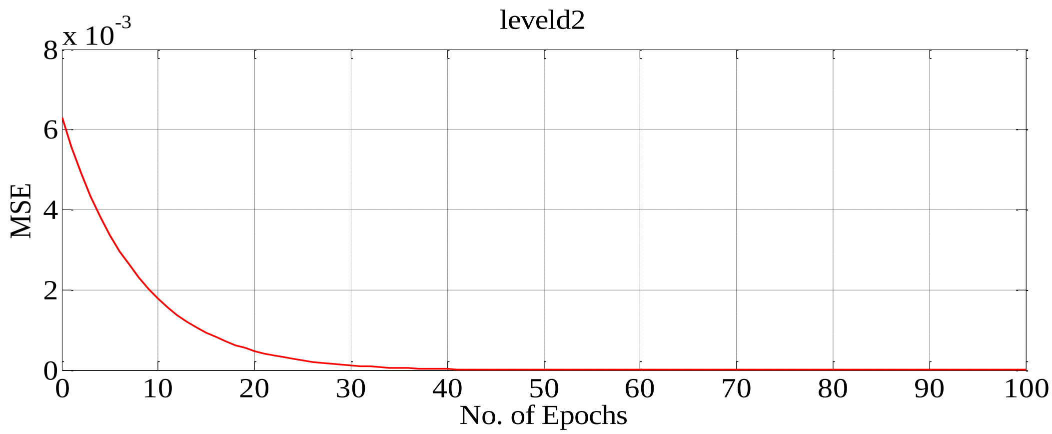

Fig.3.5.1 (b) mean square error for detail coefficients of level 2nd

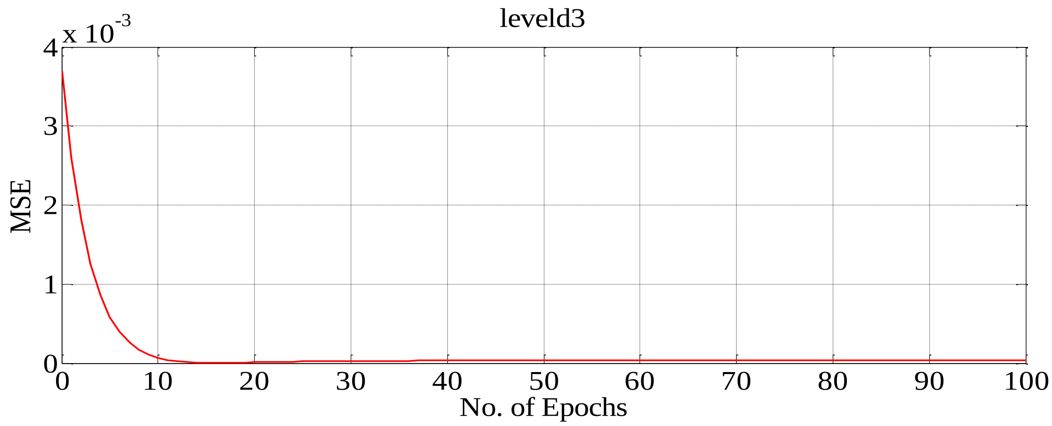

Fig.3.5.1 (c) mean square error for detail coefficients of level 3rd

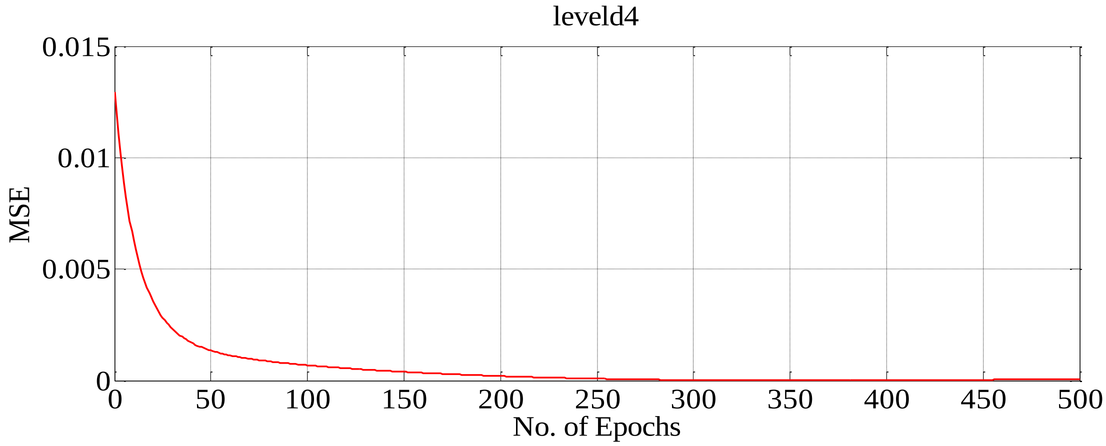

Fig.3.5.1 (d) mean square error for detail coefficients of level 4th

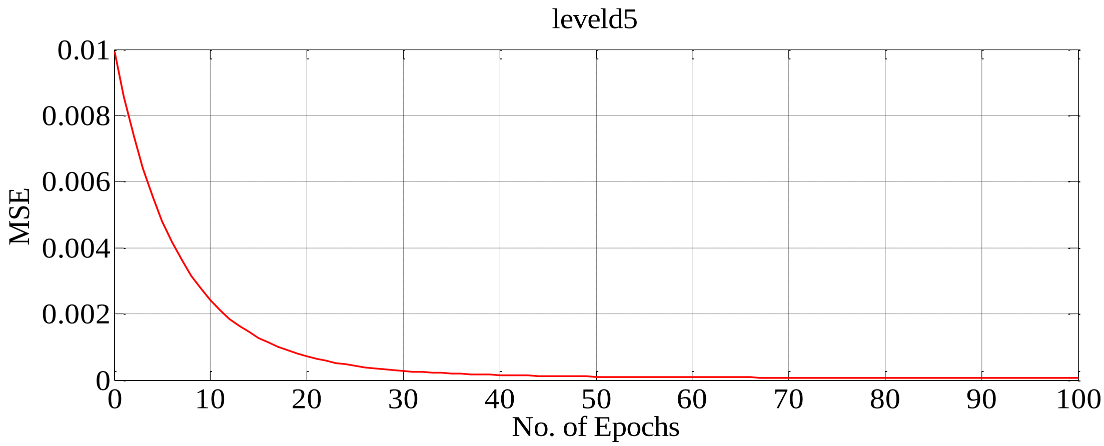

Fig.3.5.1 (e) mean square error for detail coefficients of level 5th

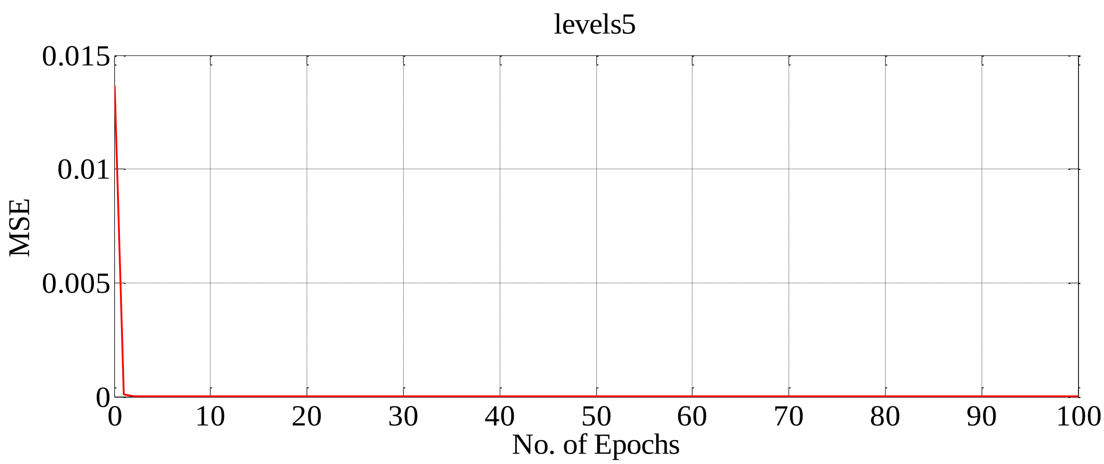

Fig.3.5.1 (f) mean square error for smooth coefficients of level 5th

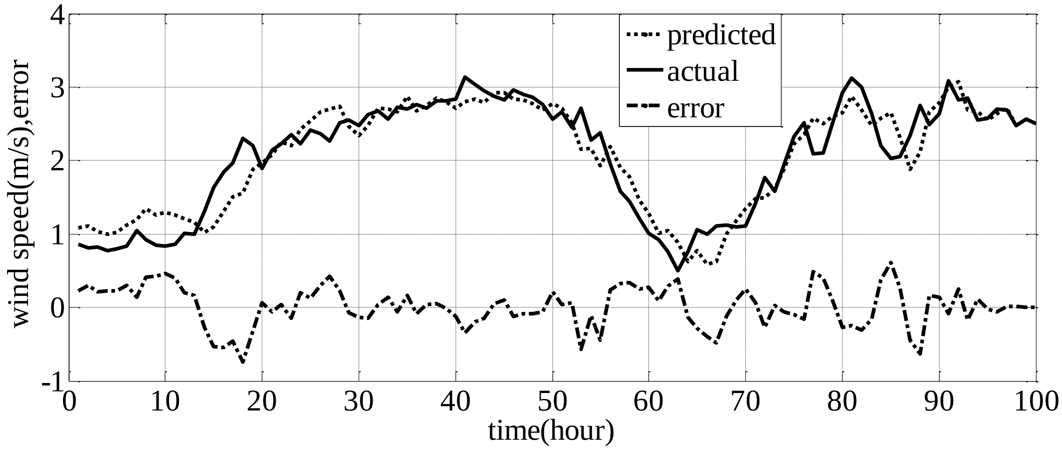

Fig.3.5.1 (g) wind speed forecast of 100 successive hours ahead forecasting with RWNN

3.5.2 Results and discussion

Wind speed estimation up to 100 successive hour ahead forecast has been carried out by RWNN forecast model which shows better results than multilayer feed-forward neural networks and AWNN. The effectiveness of the forecasting model has been studied with mean square error calculated for each level of decomposition coefficients (from Fig.3.5.1 (a)-(f)) which shows the faster convergence than other two models for forecasting. The error for the RWNN (given in Fig.3.5.1 (g)) is reduced to half of the error of the AWNN model. Performance index of this method for wind speed estimation can be calculated through mean absolute error (MAE) which is same as eq. (13), defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| = \frac{1}{n}\sum_{i=1}^{n}\left|e_i\right|$$

where $\hat{y} =$ estimated wind speed through multilayer feed-forward neural network,

$y =$ Actual wind speed,

$n =$ Number of observation, and $e =$ error signal generated

Percentage of Mean absolute error (MAE) of wind speed estimation for the recurrent wavelet neural network model has been calculated from the Fig.3.5.1 (g) as

$\%MAE = 1.14\%$.

CHAPTER 4

Conclusions and suggestions for future work

4.1 General Conclusions of the Thesis

- The wind speed data has been studied with the two wavelet techniques (DWT and MODWT) and then with the MODWT technique the available wind speed data is decomposed up to 5th level.
- Each level decomposition coefficients (detail coefficients of all the level and smooth coefficients of last 5th level) are allowed to pass through three different neural networks for estimation of wind speed.
- Each level signal has been forecasted individually and then with the inverse processes the signal reconstruction is carried out to get the original forecasted wind speed sample up to 100 consecutive hours ahead.
- Among the entire three forecast model, RWNN model performs better results (in terms of mean absolute error as the performance index) than other two models.

4.2 Suggestions for future work

- With this forecasted wind speed, wind power can be estimate.
- Comparative studies with other different methods for wind speed forecasting can be done.
- To overcome the limitation of existing approaches, with this wind speed forecasting models a control strategy can be developed.

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